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Neoclassical Factors

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Abstract

The cross section of returns can be summarized by the market factor and mimicking portfolios based on investment-to-assets and earnings-to-assets motivated from neoclassical reasoning. The neoclassical three-factor model can capture average return variations related to short-term prior returns and financial distress anomalous to traditional factor models. Our model also captures the relations of average returns with earnings-to-price, cash flow-to-price, book-to-market, dividend-to-price, long-term past sales growth, long-term prior returns, and market leverage.

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1 Introduction

The capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965) cannot explain many anomalies in the cross section of returns. For example, DeBondt and Thaler (1985), Rosenberg, Reid, and Lanstein (1985), Fama and French (1992), and Lakonishok, Shleifer, and Vishny (1994) show that average returns covary with book-to-market, earnings-to-price, cash flow-to-price, long-term past sales growth, and long-term prior returns. Jegadeesh and Titman (1993) show that stocks with higher short-term prior returns tend to have higher average returns.

Fama and French (1993, 1996) show that many of the CAPM anomalies can be captured by their three-factor model that includes the market excess return (MKT), a mimicking portfolio based on market equity (SMB), and a mimicking portfolio based on book-to-market (HML). These explained anomalies include the average return variations across portfolios formed on size and book-to-market and portfolios formed on earnings-to-price, cash flow-to-price, long-term past sales growth, and long-term prior returns. The reason is that these portfolios display strong variations in the loading on HML in the direction consistent with their average return variations.

However, the Fama-French (1993) model leaves important anomalies unexplained. Fama and French (1996) show that their model does not explain the momentum effect of Jegadeesh and Titman (1993). Stocks with low short-term prior returns tend to load positively on HML, and stocks with high short-term prior returns tend to load negatively on HML. This loading pattern goes to the opposite direction as the average-return pattern. Instead of explaining it, the Fama-French model exacerbates the momentum anomaly.

The relation between financial distress and average returns also eludes the Fama-French (1993) model. Fama and French (1996) conjecture that the average return of HML is likely to be a risk premium for the relative distress of firms. The idea is that the stocks of distressed firms tend to move together, meaning that their distress risk cannot be diversified and thus demands a risk premium. However, recent studies have shown that distress risk is related to lower average returns

(Dichev 1998; Griffin and Lemmon 2002; Campbell, Hilscher, and Szilagyi 2007). In particular, using a comprehensive measure of failure probabilities, Campbell et al. report that more distressed stocks have lower average returns despite their higher volatilities, market betas, and loadings on SMB and HML than less distress stocks. The authors conclude that: "This result is a significant challenge to the conjecture that the value and size effects are proxies for a financial distress premium. More generally, it is a challenge to standard models of rational asset pricing in which the structure of the economy is stable and well understood by investors (p. 29)."

We show that many of these anomalies are related, and are captured by a new factor model motivated from neoclassical reasoning. The model says that the expected return on a portfolio in excess of the risk-free rate, $E[R_j]-R_f$, is described by the sensitivity of its return to three factors: (i) MKT; (ii) the difference between the return on a portfolio of low investment-to-assets stocks and the return on a portfolio of high investment-to-assets stocks (INV); and (iii) the difference between the return on a portfolio of high earnings-to-assets stocks and the return on a portfolio of low earnings-to-assets stocks ($PROD$). Specifically, the expected excess return on portfolio j is given by:

$$E[R_j] - R_f = b_j\, E[MKT] + i_j\, E[INV] + p_j\, E[PROD] \tag{1}$$

where $E[MKT], E[INV]$, and $E[PROD]$ are expected premiums, and the factor loadings, b_j, i_j, and p_j are the slopes in the time-series regression:

$$R_j - R_f = a_j + b_j\, MKT + i_j\, INV + p_j\, PROD + \varepsilon_j \tag{2}$$

In our 1972–2005 sample, INV and $PROD$ earn average returns of 0.45% and 0.73% per month (t-statistics = 4.57 and 3.02), respectively. These average returns subsist after adjusting for their exposures to traditional factors such as the Fama-French (1993) three factors and the Carhart (1997) four factors. The two neoclassical factors, coupled with MKT, combine to capture much of the cross-sectional variations in average returns on NYSE, Amex, and NASDAQ stocks.

Most important, the neoclassical model outperforms the Fama-French (1993) model in capturing the average returns of the 25 size-momentum portfolios. Only the winner-minus-loser portfolio in the smallest size quintile has a significant alpha of 0.55% per month (t-statistic = 2.53). The alphas in four other size quintiles, with magnitudes ranging from 0.01% to 0.39% per month, are all insignificant. In contrast, the alphas from the Fama-French model have magnitudes ranging from 0.80% to 1.19% per month, and are all significant across the five size quintiles.

The reason for the relative success of the neoclassical model is that winners have higher loadings on $PROD$ than losers, meaning that winners tend to be more productive than losers. Somewhat surprisingly, winners also have higher loadings on INV than losers. The crux is timing. We show that winners with high valuation ratios indeed invest more than losers with low valuation ratios at the portfolio formation month t. More important, winners also invest less than losers from month t−60 to month t–8. Because INV is rebalanced annually, the higher INV-loadings for winners accurately reflect their lower investment than losers several quarters prior to the monthly portfolio formation.

The neoclassical model captures the large negative abnormal returns of the high-minus-low distress portfolios. Intuitively, less distressed firms are more productive and load more on $PROD$, and more distress firms are less productive and load less on $PROD$. By ignoring the effects of productivity on expected returns, traditional factor models fail to explain the distress anomaly. The $PROD$ loadings also allow our model to capture the abnormal returns across portfolios formed on returns on assets (ROA) and on Standardized Unexpected Earnings (SUE) (Bernard and Thomas 1989; Piotroski 2000). The model reduces the alpha of the high-minus-low ROA portfolio to an insignificant 0.12% per month, although the alpha of the high-minus-low SUE decile is still 0.74% (t-statistic = 4.86). However, the SUE alpha represents a reduction of about 30% relative to the alphas of 1.07% in the CAPM and 1.09% in the Fama-French (1993) model.

Finally, the neoclassical model captures well the average return variations across other testing portfolios in Fama and French (1996). These portfolios are formed on size and book-to-market and on earnings-to-price, cash flow-to-price, dividend-to-price, long-term past sales growth, long-term prior returns, and market leverage. While the Fama-French model achieve this feat through their

HML factor, the main driving force in our model is the INV factor. Stocks with high fundamental-to-price ratios (including market leverage measured as assets-to-market), low long-term past sales growth, and low long-term prior returns invest less, load more on the low-minus-high INV factor, and thus earn higher average returns than stocks with low fundamental-to-price ratios, high long-term past sales growth, and high long-term prior returns.

At a minimum, our empirical results show that the cross section of returns can, for the most part, be summarized by the neoclassical three-factor model. This evidence, coupled with the motivation of our factors from equilibrium asset pricing theory, suggests that the neoclassical model can be used in many applications that require estimates of expected stock returns. The list includes evaluating mutual fund performance, measuring abnormal returns in event studies, and estimating expected returns for portfolio choice and costs of capital for capital budgeting.

Our empirical work is guided by recent developments in investment-based asset pricing. Cochrane (1991) use the q-theory to study aggregate stock returns. Zhang (2005) uses a full-fledged industry equilibrium model to study the value premium. Li, Livdan, and Zhang (2007) use a related model augmented with costly external finance to study the external financing anomalies. Liu, Whited, and Zhang (2007) use the q-theory to develop characteristics-based expected-return models that can be estimated via GMM. A related line of study is pursued by Berk, Green, and Naik (1999) and Carlson, Fisher, and Giammarino (2004, 2006) using the real options framework.

Several other papers also bring investment-based asset pricing theories to bear on empirical finance. Anderson and Garcia-Feijóo (2006) report that investment growth conditions subsequent classifications of firms to portfolios formed on size and book-to-market. Xing (2006) shows that an investment growth factor can explain the value effect in asset pricing tests as well as HML. Lyandres, Sun, and Zhang (2007) show that the investment factor goes a long way in capturing the new issues puzzle of Ritter (1991) and Loughran and Ritter (1995). Wu, Zhang, and Zhang (2007) show that investment is also likely to drive Sloan's (1996) accrual anomaly. We aim to provide a parsimonious multi-factor model that can capture the cross-sectional variations of average returns.

Fama and French (2006) use valuation theory to link expected returns to book-to-market, expected profitability, and expected investment. Controlling for the other two variables, more profitable firms earn higher expected returns, as do firms with higher book-to-market. Their tests confirm these predictions. We derive these predictions, among others, from neoclassical economics, and we relate them to momentum and financial distress anomalies not addressed by Fama and French.

Section 2 motivates the neoclassical factors. Sections 3 and 4 document that the neoclassical model captures many anomalies missed by traditional factor models. We trace the explanatory power of our model to economic fundamentals in Section 5. We interpret our results in Section 6.

2 Hypothesis Development and Empirical Design

Sections 2.1 and 2.2 develop testable hypotheses, and Section 2.3 discusses our empirical approach.

2.1 The Investment Hypothesis

We derive testable hypotheses using a simple two-period q-theory model à la Cochrane (1991, 1996). Using this model, we derive a purely characteristics-based expected-return model (see Appendix A):

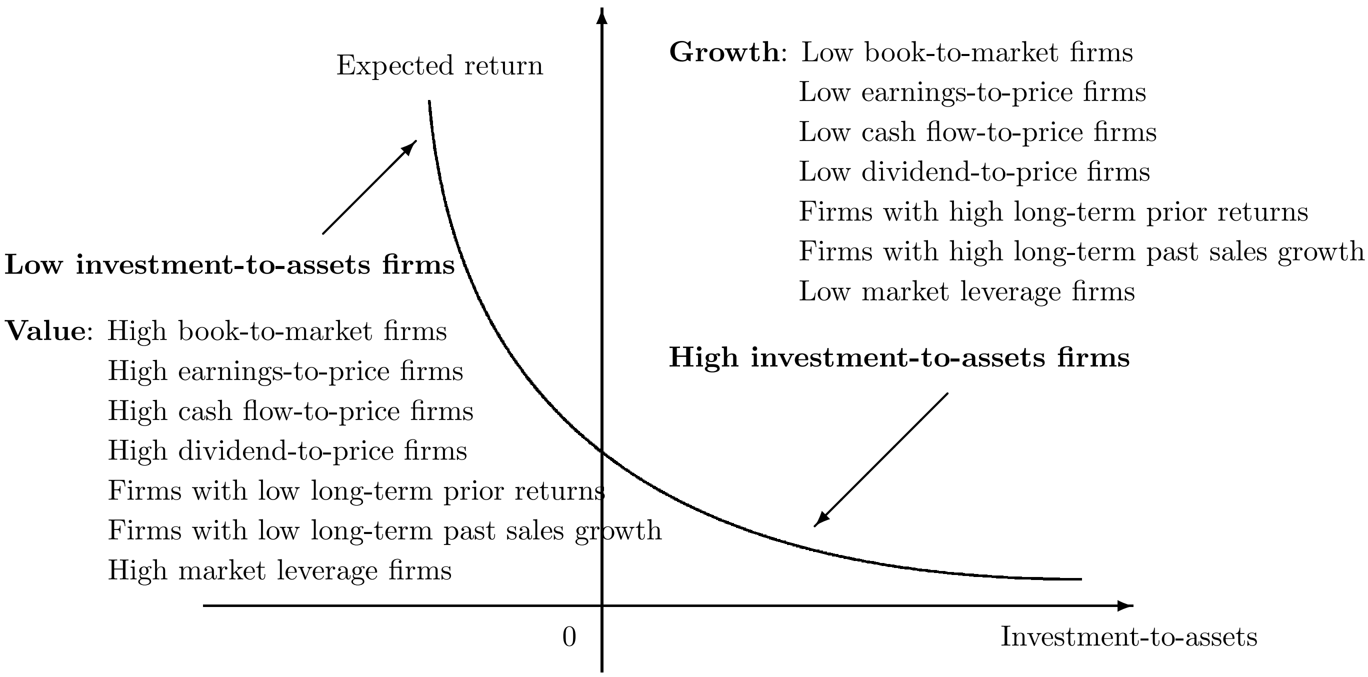
$$\text{Expected return} = \frac{\text{Expected profitability} + 1}{\text{Marginal cost of investment}} \tag{3}$$

Basically, the expected return is the ratio of expected profitability divided by marginal cost of investment. This equation is useful for understanding asset pricing anomalies because it ties expected stock returns directly to firm characteristics. In particular, investment-to-assets and expected profitability are two important economic determinants of expected returns.

Intuition

Equation (3) says that expected returns are negatively correlated with investment-to-assets, given expected proftability. The intuition is easy to understand in the capital budgeting language of Brealey, Myers, and Allen (2006). Given expected cash flows, high costs of capital imply low net present values of new capital, which in turn imply low investment-to-assets. Low costs of capital imply high net present values of new capital, which in turn imply high investment-to-assets ratios. Figure 1 illustrates the negative relation between investment-to-assets and expected returns.

Figure 1 : The Investment Story in the Cross Section of Returns



Portfolio Implications

Figure 1 shows that investment is the common driving force of many asset pricing anomalies. First, the link between book-to-market and investment-to-assets follows directly from the q theory. Optimal investment implies that investment-to-assets is an increasing function of marginal q, which is basically the average q and market-to-book.[1] Because of the negative investment-return relation, high book-to-market firms earn higher average returns than low book-to-market firms.

Other valuation ratios besides book-to-market also capture growth opportunities, and are connected to investment policy. Low cash flows relative to market equity tend to signal high growth opportunities. These firms tend to invest more and earn lower expected returns. The same intuition applies to other valuation ratios such as earnings-to-price and dividend-to-price ratios.

[1] More precisely, the marginal q equals the average q under constant returns to scale, as shown in Hayashi (1982). The average q and market-to-book equity are in turn highly correlated, and are identical in models without debt financing. See Liu, Whited, and Zhang (2007) for detailed derivations.

We also include market leverage into this category. We measure market leverage as the ratio of total assets to market equity following Fama and French (1992). Because market equity is in the denominator, high market leverage signals low growth opportunities, low investment-to-assets, and high expected returns. Low market leverage signals high growth opportunities, high investment-to-assets, and low expected returns. Gomes and Schmid (2006) formalize this intuition.

The investment story differs from the leverage story in standard corporate finance textbooks. The leverage story argues that high market leverage means high proportion of assets risk shared by equity holders, and thus high expected equity returns. This story assumes that investment policy is fixed, meaning that the assets risk does not vary with investment. In contrast, the investment story allows investment and leverage to be jointly determined, giving rise to a negative relation between market leverage and investment-to-assets.

Finally, high valuation ratios are likely to result from a string of positive shocks on economic fundamentals, which are in turn positively correlated with contemporaneous shocks on returns. This intuition suggests that the high valuation ratios of growth firms can be manifested as high past sales growth and high long-term prior returns. Similarly, the low valuation ratios of value firms can be manifested as low past sales growth and low long-term prior returns. Following Fama and French (1996), we measure long-term prior returns using the prior 13–60 month returns to be separated from the momentum effect of Jegadeesh and Titman (1993). In all, firms with high prior long-term returns and sales growth should have higher valuation ratios, invest more, and earn lower average returns than firms with low prior long-term returns and sales growth. To summarize:

HYPOTHESIS 1: *The negative relation between investment-to-assets and average returns is the common driving force of the positive relations of average returns with book-to-market, earnings-to-price, cash flow-to-price, dividend-to-price, and market leverage as well as the negative relations of average returns with prior long-term returns and past sales growth. Controlling for investment-to-assets should greatly attenuate these effects.*

Discussion

Noteworthy, the investment story is conditional on expected profitability. Equation (3) says that expected returns are negatively correlated to investment-to-assets, given expected profitability. This point is important because expected profitability is not disconnected from investment-to-assets. In fact, more profitable firms invest more than less profitable firms both in the data (e.g., Fama and French 1995) and in simulated models (e.g., Zhang 2005).

The conditional nature of the investment-return relation offers the following portfolio interpretation of Hypothesis 1. Sorting on book-to-market, earnings-to-price, cash flow-to-price, dividend-to-price, market leverage, prior long-term returns, and prior long-term sales growth is closer to sorting on investment-to-assets than sorting on expected profitability. That is, these sorts generate higher magnitudes of spread in investment-to-assets than in expected profitability. Consequently, we can interpret the average-return patterns generated from these diverse sorts using their common implied sort on investment-to-assets, as shown in Figure 1.

2.2 The Productivity Hypothesis

We stress the conditional nature of the investment hypothesis because equation (3) implies another conditional hypothesis: Given investment-to-assets, firms with high expected profitability should earn higher expected returns than firms with low expected profitability.

Intuition

As noted, marginal cost of investment equals marginal q, which is basically average q or market-to-book. From equation (3), the expected return equals the expected profitability divided by market-to-book. Intuitively, high expected profitability relative to low market valuation means high discount rate, and low expected profitability relative to high market valuation means low discount rate.

This implication of the neoclassical q-theory can be connected to the Ohlson (1995) residual income model. The Ohlson model says that:

$$\frac{P_t}{B_t} = 1 + \frac{\sum_{j=1}^{\infty} E[Y_{t+j} - rB_{t+j-1}]/(1+r)^j}{B_t} \tag{4}$$

where B_t is book equity at time t, Y_{t+j} is earnings at $t+j$, $Y_{t+j} - rB_{t+j-1}$ is the residual income defined as the difference between earnings and the opportunity cost of capital, and r is the long-term expected stock return. Fama and French (2006) derive testable hypotheses based on equation (4): Controlling for book-to-market and expected growth in book equity, more profitable firms—firms with higher expected earnings relative to current book equity—have higher expected returns. Tests conducted by Fama and French confirm this prediction.

We can also rewrite equation (3) as:

$$\text{Expected return} = (1 + \text{Expected profitability})\frac{\text{Book Equity}}{\text{Market Equity}} \tag{5}$$

which implies that the positive relation between expected returns and book-to-market is stronger among firms with higher expected profitability. This prediction helps interpret the evidence documented by Piotroski (2000) that the mean return earned by a high book-to-market investor can be increased by at least 7.5% per annum through the selection of financially strong high book-to-market firms. Piotroski constructs a composite financial performance index that includes profitability as a main component. Because of the high persistence in profitability—Fama and French (2006) show that current profitability is the strongest predictor of future profitability, current profitability is closely correlated with expected profitability, to which equation (3) applies.

Portfolio Implications

The positive profitability-return relation has important portfolio implications. For any sorts that generate higher magnitudes of spread in profitability than in investment-to-assets, their average-return patterns can be interpreted using the positive profitability-return relation.

We explore three such sorts. These are sorts on earnings, on short-term prior returns, and on financial distress measures. Sorting on ROA and SUE naturally generate spreads in profitability between extreme portfolios. Sorting on prior 2–12 month returns is also likely to generate economically important spreads in profitability. The reason is that shocks to earnings are positively correlated with contemporaneous shocks to returns. Positive shocks to earnings tend to increase current stock returns, and negative shocks to earnings tend to decrease current stock returns.

The distress anomaly is likely to be another manifestation of the positive profitability-return relation. Less distressed firms are more profitable and should earn higher average returns, even though they are less levered, and more distressed firms are less profitable and should earn lower average returns, even though they are more levered. Previous studies have ignored the effects of profitability on expected returns, and thus found the evidence anomalous. To summarize:

HYPOTHESIS 2: *The positive relation between profitability and average returns is the common driving force of the positive relations of average returns with earnings-to-assets, earnings surprises, and prior short-term returns as well as the negative relations of average returns with distress measures such as Campbell, Hilscher, and Szilagyi's (2007) failure probability and Ohlson's (1980) O-score. Controlling for profitability should greatly attenuate these anomalies.*

2.3 Empirical Design

There are several ways to explore the empirical foundation of the neoclassical theory of expected returns given by equation (3). One approach, pursued by Zhang (2005) and Li, Livdan, and Zhang (2007), is to construct full-fledged equilibrium models, solve them numerically, and simulate them to see if the model-implied moments can match the key stylized facts in the data. This quantitative theory approach à la Kydland and Prescott (1982) is useful to understand important economic driving forces and the mechanisms through which they work. However, this approach does not provide an easy-to-use empirical model for calculating costs of capital in practice.

Another approach, pursued by Liu, Whited, and Zhang (2007), is to parameterize the production and investment technologies of firms, construct the right hand side of the dynamic version of equation (3), and then use GMM to minimize the differences between the average stock returns and the average ratios in the right hand side. This structural estimation approach à la Hansen and Singleton (1982) has the advantage of being closely linked to the underlying economic theory. This approach does provide an empirical model of expected returns. However, it is more complicated to implement than the models commonly used in empirical finance.

We adopt the Fama-French (1993) portfolio approach to explore our testable hypotheses. Although the link to the underlying economic theory is less direct, this approach is intuitive and simple to use on a large set of testing portfolios. The widespread use of this approach also allows us to compare our empirical results easily to the results from the prior literature.

We construct factor mimicking portfolios based on investment-to-assets and profitability, which, according to equation (3), are important economic determinants of expected returns. We call these mimicking portfolios the investment factor, INV, and the productivity factor, $PROD$, respectively. Because these two factors are derived from the partial equilibrium q-theory that studies the optimal behavior of firms, we also include the market factor, MKT, which can be derived from the partial equilibrium theory of consumption (see, for example, Cochrane 2005, p. 155–156). The resulting three-factor specification ($MKT + INV + PROD$), dubbed the neoclassical three-factor model, can be interpreted as motivated from the Arrow-Debreu general equilibrium theory.

We use the neoclassical three-factor model as a parsimonious and practical model for estimating expected returns. In the same way that Fama and French (1996) test their three-factor model, we regress returns of a wide range of testing portfolios in excess of the risk-free rate on the neoclassical three factor returns as in equation (2). If the neoclassical model adequately describes the cross section of returns, then the intercepts should be statistically indistinguishable from zero.

3 Tests on the Value and Momentum Portfolios

3.1 The Inputs to the Time-Series Regressions

The explanatory variables in the time-series regressions include MKT, INV, and $PROD$. The returns to be explained are 25 portfolios formed on size and book-to-market equity and 25 portfolios formed on size and prior short-term returns. We choose to start with value and momentum portfolios because these are arguably the two most important stylized facts in the cross section of returns.

The Explanatory Factors

We obtain monthly returns, dividends, and prices from the Center for Research in Security Prices (CRSP) and accounting information from the COMPUSTAT Annual and Quarterly Industrial Files. The sample is from January 1972 to December 2005. The starting date of the sample is restricted by the availability of quarterly earnings data. We exclude financial firms and firms with negative book value of equity. Also, only firms with ordinary common equity are included in the tests, so ADRs, REITs, and units of beneficial interest are excluded.

Following the Fama and French (1993) portfolio approach, we construct INV as the zero-cost portfolio long in stocks with the lowest 30% investment-to-assets ratios and short in stocks with the highest 30% investment-to-assets ratios. We do a double sort on size and investment-to-assets. In June of each year t from 1972 to 2005, all NYSE stocks on CRSP are sorted on market equity (price times number of shares). We use the median NYSE size to split NYSE, Amex, and NASDAQ stocks into two groups. We also break NYSE, Amex, and NASDAQ stocks into three investment-to-assets (I/A) groups based on the breakpoints for the low 30%, middle 40%, and high 30% of the ranked values for stocks traded on all three exchanges. We form six portfolios from the intersections of the two size and the three I/A groups. Monthly value-weighted returns on the six portfolios are calculated from July of year t to June of $t+1$, and the portfolios are rebalanced in June of $t+1$. We calculate returns beginning in July of year t to ensure that investment for year $t-1$ is known. The INV factor is designed to mimic the common variations in returns related to investment-to-assets. INV is the difference (low-minus-high investment), each month, between the simple average of the returns on the two low-I/A portfolios and the simple average of the returns on the two high-I/A portfolios.

We measure investment-to-assets as the annual change in gross property, plant, and equipment (COMPUSTAT annual item 7) plus the annual change in inventories (item 3) divided by the lagged book value of assets (item 6). Changes in property, plant, and equipment capture capital investment in long-lived assets used in operations over many years such as buildings, machinery, furniture, and other equipment. And changes in inventories capture capital investment in short-lived assets used in a normal operating cycle such as merchandise, raw materials, supplies, and work in progress.

Table 1 reports that the average return of INV in our sample is 0.45% per month (t-statistic = 4.57). Regressing INV on the market factor generates an alpha of 0.53% per month (t-statistic = 5.72). Adjusting for the Fama and French (1993) three factors and the Carhart (1997) four factors reduces the alpha to 0.36% and 0.25% per month, respectively, both of which remain significant. The data for the Fama-French factors and the momentum factor are from Kenneth French's Web site. The evidence suggests that INV captures some average return variations not subsumed by the other well-known factors. INV also has a high correlation of 0.46 with HML, which is significant at the 1% level. This evidence is consistent with Xing (2006), who shows that an investment growth factor contains information similar to HML and can explain the value effect roughly as well as HML. Xing constructs her investment-related factor by sorting on the growth rate of capital expenditure (COMPUSTAT annual item 128). The average return of her factor is only 0.20% per month, albeit significant at 1% level. We use a more comprehensive measure of capital investment, following Lyandres, Sun, and Zhang (2007), and our investment factor earns a higher average return.

We construct the productivity factor, $PROD$, based on earnings-to-assets, ROA. Untabulated results show that using cash-flow-to-assets to measure productivity does not materially affect our results. $PROD$ is the zero-cost portfolio long in stocks with the highest 30% values of ROA and short in stocks with the lowest 30% values of ROA. We do a double sort on size and ROA. Because $PROD$ is most relevant for understanding the momentum strategies that are typically rebalanced monthly, we use a similar approach to construct $PROD$ and use quarterly data to measure ROA. ROA is the quarterly earnings (COMPUSTAT quarterly item 8) divided by last quarter's assets (item 44, plus the difference between market equity and book equity multiplied by 0.10). Our calculation of assets, borrowed from Campbell, Hilscher, and Szilagyi (2007), is meant to mitigate the impact of assets that are close to zero when used to calculate ROA.

At the beginning of each month from January 1972 to December 2005, we categorize NYSE, Amex, and NASDAQ stocks into three groups based on the breakpoints for the low 30%, middle 40%, and high 30% of the ranked values of quarterly ROA from at least four months ago for stocks traded on all three exchanges. The choice of the four-month lag is conservative; choosing shorter lags such as the most recent ROA only serves to strengthen our results. We choose the four-month lag to ensure that the accounting information is available before we form the portfolios.

Also, in each June, we sort all NYSE stocks on size and use the median to split NYSE, Amex, and NASDAQ stocks into two groups. From the intersections of the two size and three ROA groups, we form six portfolios. Monthly value-weighted returns on the six portfolios are calculated for the current month, and the portfolios are rebalanced monthly. The $PROD$ factor is meant to mimic the common variations in returns related to firm-level productivity, and is defined as the difference (high-minus-low productivity), each month, between the simple average of the returns on the two high-ROA portfolios and the simple average of the returns on the two low-ROA portfolios.

Table 1 reports that the average return of $PROD$ from January 1972 to December 2005 is 0.73% per month (t-statistic = 3.02). Adjusting for the market factor, the Fama and French (1993) three factors, and the Carhart (1997) four factors yields alphas of 0.81%, 0.79%, and 0.52% per month, all of which are significant. This evidence suggests that, like INV, $PROD$ also captures some average return variations not subsumed by the other well-known factors. Further, the correlation between INV and $PROD$ is only 0.05 (the p-value of testing zero correlation = 0.33). We thus see no need to neutralize INV and $PROD$ against each other.

The Returns To Be Explained

The first set of returns to be explained includes 25 portfolios formed on size and book-to-market equity (BE/ME) and 25 portfolios formed on size and prior 2–12 month returns (momentum). We obtain returns on these portfolios from Kenneth French's Web site.

Table 2 reports the summary statistics and traditional factor regressions on the 25 size-BE/ME portfolios and the 25 size-momentum portfolios. From Panel A, value stocks earn higher average returns than growth stocks. The average high-minus-low return is higher in small firms: 1.08% per month (t-statistic = 4.90) in the smallest size quintile versus 0.21% per month (t-statistic = 0.99) in the biggest size quintile. The CAPM cannot explain the value premium. The high-minus-low strategies have significantly positive alphas in four of out five size quintiles, despite their significantly negative market betas. For example, the strategy in the smallest size quintile has a positive alpha of 1.30% per month (t-statistic = 6.81) despite a negative beta of -0.45.

Consistent with Fama and French (1996), their three-factor model captures most of the variations across the average returns on the 25 size-BE/ME portfolios. The reason is that their model generates systematic variations in factor loadings: Small stocks have higher loadings on SMB than big stocks, and value stocks have higher loadings on HML than growth stocks. The average of the 25 regression R^2 is 0.91, so small intercepts are often distinguishable from zero. However, the Fama-French model leaves an economically sizable intercept of -0.52% per month for the portfolio of stocks in the smallest size and lowest BE/ME quintiles.

Panel B of Table 2 reports that the momentum strategy is profitable, especially in small firms. The winner-minus-loser average returns vary from 1.00% per month (t-statistic = 5.09) in the smallest size quintile to 0.64% per month (t-statistic = 1.95) in the biggest size quintile. The CAPM alphas for the winner-minus-loser strategies are all significantly positive, despite their negative market betas. Consistent with Fama and French (1996), their three-factor model exacerbates the momentum puzzle. The intercepts for the winner-minus-loser portfolios from their model are universally higher than their corresponding CAPM alphas. The reason is that losers have higher loadings on HML than winners: Losers behave more like value stocks, so the Fama-French model predicts that they should earn higher average returns, instead of lower average returns we see in the data.

3.2 Neoclassical Factor Regressions

Our neoclassical three-factor model performs roughly as well as the Fama-French (1993) model in capturing the average returns of the 25 size-BE/ME portfolios. More important, our model outperforms the Fama-French model in pricing the 25 size-momentum portfolios.

Neoclassical Three-Factor Regressions: The 25 Size-BE/ME Portfolios

In Panel A of Table 3, we regress the 25 size-BE/ME portfolio excess returns on the MKT, INV, and $PROD$ returns. The model does a good job in pricing these portfolios. The zero-cost high-minus-low strategy in the smallest size quintile has a significant alpha of 0.71% per month (t-statistic = 3.46). But the high-minus-low alphas in all other four size quintiles, with magnitudes ranging from 0.00 to 0.32% per month, are all insignificant. This performance is an improvement over the Fama-French (1993) model, which predicts a relatively large negative alpha of −0.45% per month (t-statistic = −3.37) for the high-minus-low strategy in the biggest size quintile (see Table 2, Panel A). In particular, the Fama-French model generates an alpha of 0.18% per month (t-statistic = 2.82) for the portfolio of stocks in the biggest size and lowest BE/ME quintiles and an alpha of −0.27% per month (t-statistic = −2.35) for the portfolio of stocks in the biggest size and highest BE/ME quintiles. Both portfolios have small and insignificant alphas in our model.

The loadings on INV and on $PROD$ shed light on the explanatory power of the neoclassical factor model for the 25 size-BE/ME portfolios. From Panel A of Table 3, value stocks have higher loadings on INV than growth stocks, and the loading spreads ranging from 0.52 to 0.77 are all significant. Because INV is long in low-investment stocks and short in high-investment stocks, the evidence suggests that growth firms tend to invest more than value firms. Somewhat surprisingly, value stocks also have mostly higher loadings on $PROD$ than growth stocks. Except for the biggest size quintile, the high-minus-low loadings on $PROD$ are all significantly positive, and their magnitudes from 0.22 to 0.40 are economically important. Because $PROD$ is long in high-productivity stocks and short in low-productivity stocks, the evidence suggests that value firms can be more productive than growth firms. We show in Section 5 that the difference is driven by the abnormally low profitability of small firms that also have low BE/ME ratios in the past decade. Most important, because INV and $PROD$ both earn positive average returns, their loadings go in the right direction in explaining the value premium.

However, the Fama-French (1993) model outperforms our model in two aspects. First, the average magnitude of the 25 alphas in their model is 0.12% per month, which is only one half of the average magnitude of the 25 alphas from the neoclassical regressions, 0.24%. Moreover, the average R^2 from the Fama-French regressions is 0.91, and that in our neoclassical regressions is 0.74. But the characteristics on which we construct our explanatory factors are different from the characteristics on which we construct the portfolio returns to be explained.

Neoclassical Three-Factor Regressions: The 25 Size-Momentum Portfolios

Our model outperforms the Fama-French (1993) model in pricing the 25 size-momentum portfolios. From Panel B of Table 3, only the winner-minus-loser strategy in the smallest size quintile has a significant alpha of 0.55% per month (t-statistic = 2.53). The alphas in other size quintiles, from 0.01% to 0.39% per month, are all insignificant. In contrast, Table 2 shows that the Fama-French (1993) alphas have magnitudes from 0.80% to 1.19% per month that are significant across all five size quintiles. The average magnitude of the 25 neoclassical alphas is 0.42% per month, about 41% lower than the average magnitude of the 25 Fama-French alphas, 0.70% per month.

Both INV and $PROD$ loadings go in the right direction in capturing the average winner-minus-loser returns. From Panel B of Table 3, winners have higher loadings on $PROD$ than losers across the five size quintiles, and the loading spreads from 0.28 to 0.41 are all significant. This evidence suggests that winners tend to be more productive than losers. Noteworthy, winners also have higher loadings on INV than losers. This finding is initially surprising. One would expect that winners with high stock valuation ratios should invest more and have lower loadings on INV than losers with low stock valuation ratios. The crux is timing. We show in Section 5 that winners indeed have higher contemporaneous investment-to-assets ratios than losers at the month of portfolio formation. But more important, winners also have lower investment-to-assets ratios than losers starting from two to four quarters prior to the portfolio formation. Because INV is rebalanced annually, the higher loadings of INV for winners accurately reflect their lower investment-to-assets ratios than losers several quarters prior to the monthly portfolio formation of momentum strategies.

Alternative Factor Specifications

To study the individual role of the neoclassical factors, we explore two alternative two-factor specifications: $MKT+INV$ and $MKT+PROD$. INV and $PROD$ both reduce the overall magnitudes of the alphas. However, their individual roles differ: INV is more important in pricing the 25 size-BE/ME portfolios, and $PROD$ is more important in pricing the 25 size-momentum portfolios.

Table 4 reports the alternative regressions. Value stocks continue to have higher loadings on INV, and for the most part, higher loadings on $PROD$ than growth stocks. INV helps reduce overall magnitude of the alphas for the 25 size-BE/ME portfolios. The average magnitude of the 25 alphas from the two-factor regressions with MKT and INV is 0.22% per month, which is comparable to the average magnitude of the alphas from the benchmark three-factor regressions, 0.24%. The average magnitude of the alphas from the two-factor regressions with MKT and $PROD$ is 0.32% per month, which is about 35% higher than the average magnitude of the alphas from the benchmark model. For the high-minus-low strategies across the five size quintiles, their average alpha is 0.28% per month in the benchmark three-factor model, 0.45% in the two-factor $MKT+INV$ model, and is 0.64% in the two-factor $MKT+PROD$ model. INV thus seems more important than $PROD$ in driving the average returns of the size-BE/ME portfolios.

However, the data present a more complicated picture. $PROD$ helps reduce the large negative alpha for the portfolio that contains stocks in the smallest size quintile and in the lowest BE/ME

quintile. This alpha is a tiny -0.05% per month (t-statistic $= -0.19$) in the benchmark three-factor model, -0.59% (t-statistic $= -2.29$) in the two-factor $MKT+INV$ model, and -0.10% (t-statistic $= -0.39$) in the two-factor $MKT+PROD$ model. The importance of $PROD$ in pricing this portfolio is related to its abnormally low profitability in the past decade, as we show later in Section 5.

Panel B of Table 4 reports the alternative factor regressions for the 25 size-momentum portfolios. $PROD$ tends to contribute more than INV in reducing the overall magnitude of the alphas, although winners continue to have higher loadings on both INV and $PROD$. The average magnitude of the 25 alphas in the two-factor model with MKT and $PROD$ is 0.41% per month, similar to the magnitude of 0.42% in the benchmark model, but is lower than the magnitude of 0.50% per month in the two-factor model with MKT and INV. The data again tell a more complicated story: INV and $PROD$ are both responsible for the relatively low magnitudes of the winner-minus-loser alphas across the five size quintiles. The average winner-minus-loser alpha is 0.26% per month in the benchmark three-factor model, but is above 0.50% in both two-factor models.

4 Tests on Additional Portfolios

Section 4.1 shows that the neoclassical model captures the distress anomaly missed by the Fama-French (1993) model. Section 4.2 shows that the model makes some progress in the context of the notorious earnings anomalies. And Section 4.3 shows that our model does roughly as well as the Fama-French model in pricing alternative value portfolios.

4.1 Tests on the Distress Portfolios

The testing portfolios include the ten deciles sorted on the failure probability measure (F-Prob) of Campbell, Hilscher, and Szilagyi (2007) and the ten deciles sorted on the O-Score from Ohlson (1980). We follow Campbell et al. and Ohlson closely in constructing the distress measures (see Appendix B for details). We also have experimented with Altman's (1968) Z-score, but the CAPM explains well the average returns of the Z-score deciles. Untabulated results also show that the high-minus-low Z-score portfolio has an insignificant alpha in the neoclassical three-factor regression but a significant positive alpha from the Fama-French (1993) model.

Table 5 reports the tests on the F-Prob and O-score portfolios. Consistent with Campbell, Hilscher, and Szilagyi (2007), high F-Prob firms earn lower average returns than low F-Prob firms. The average-return spread of -0.45% per month is insignificant, but the CAPM alpha for the high-minus-low F-Prob portfolio is -0.77% (t-statistic $= -2.10$). The alpha is large and negative even though its beta is significantly positive, 0.56 (t-statistic $= 5.85$). The alpha from the Fama-French (1993) model is similar, -0.88% per month (t-statistic $= -2.51$). In contrast, the neoclassical model generates an insignificant alpha of 0.36% per month for the high-minus-low F-Prob portfolio. The two extreme F-Prob deciles have similar loadings on INV, so the driving force for the model performance is the large negative $PROD$-loading spread of -1.30 (t-statistic $= -10.69$).

The results from the O-score portfolios are more dramatic. The high O-score portfolio underperforms the low O-score portfolio by an average of -0.80% per month (t-statistic $= -2.41$). Paradoxically, the high O-score portfolio has a higher market beta than the low O-score portfolio, 1.33 versus 1.03. Adjusting for market beta thus exacerbates the puzzle: The alpha of the high-minus-low O-score portfolio is -0.95% per month (t-statistic $= -3.00$). Adjusting for the Fama and French (1993) factors makes things worse. The high O-score portfolio has higher loadings on both SMB and HML, giving rise to an alpha of -1.35% per month (t-statistic $= -6.07$) for the high-minus-low portfolio. More important, the neoclassical three-factor model eliminates the abnormal return: The intercept is reduced to a tiny -0.14% per month (t-statistic $= -0.48$). The driving force is again the large negative $PROD$-loading for the high-minus-low O-score portfolio. In all, our evidence suggests that the distress anomaly is just another manifestation of the positive ROA-return relation; once productivity is controlled for, the anomaly largely disappears.

4.2 Tests on the Earnings Portfolios

The earnings anomaly is important. For example, Fama (1998, p. 286) writes that: "The granddaddy of underreaction events is the evidence that stock prices seem to respond to earnings for about a year after they are announced (Ball and Brown 1968; Bernard and Thomas 1990)." We show that the neoclassical model outperforms traditional factor models in capturing the earnings anomalies.

To construct testing portfolios related to earnings, we sort stocks on two characteristics: ROA and SUE. As noted, ROA is the quarterly earnings (COMPUSTAT quarterly item 8) divided by one-quarter-lagged assets (item 44, plus the difference between market equity and book equity multiplied by 0.10). At the beginning of every month from January 1972 to December 2005, we sort NYSE, Amex, and NASDAQ stocks into ten deciles based on the breakpoints of the ranked quarterly ROA from at least four months ago for stocks traded on all three exchanges. Monthly value-weighted returns on the ten portfolios are calculated for the current month. To construct the SUE deciles, we rank all NYSE, Amex, and NASDAQ stocks at the beginning of every month by their most recent past SUE. SUE is measured as unexpected earnings (the change in quarterly earnings per share from its value four quarters ago) divided by the standard deviation of unexpected earnings over the last eight quarters. The assignment uses NYSE, Amex, and NASDAQ breakpoints, and the portfolios are value-weighted.

Table 6 reports the test results. From Panel A, the high-ROA decile earns higher average returns than the low-ROA decile, and the difference of 0.99% per month is significant at the 1% level. The high-ROA decile also has lower market beta and lower loadings on SMB and HML than the low-ROA decile. Adjusting for the CAPM and the Fama-French (1993) three factors thus gives rise to even higher abnormal returns for the high-minus-low ROA portfolio, 1.14% and 1.30% per month (t-statistics = 3.77 and 4.79), respectively. More important, the high-minus-low ROA portfolio earns a small alpha of 12 basis points per month (t-statistic = 0.55) in the neoclassical regression. The two extreme deciles have largely the same INV-loadings, but the $PROD$-loading spread between them is a sizable 1.25 (t-statistic = 12.16). This higher $PROD$-loading spread drives away the ROA anomaly of Haugen and Baker (1996).

From Panel B of Table 6, sorting on SUE produces an average-return spread of 1.06% per month (t-statistic = 6.71) between the two extreme deciles. The neoclassical model reduces the intercept from 1.09% in the Fama-French model to 0.74% per month, a reduction in magnitude of 32%. But the alpha remains significant. The intercept is lower because the high-minus-low SUE portfolio has a positive INV-loading of 0.24 and a positive $PROD$-loading of 0.25, both of which are significant.

4.3 Tests on Additional Value Portfolios

Fama and French (1996) show that, except for momentum, their three-factor model captures well average return variations across portfolios sorted on earnings-to-price (E/P), cash flow-to-assets (C/P), dividend-to-price (D/P), past sales growth, and long-term prior returns. The performance of the neoclassical factor model in explaining these average return variations is largely comparable to the performance of the Fama-French model. For ease of comparison with Fama and French (1996), we use portfolio data from Kenneth French's Web site whenever possible. French provides portfolio data for the one-way deciles sorted on $E/P, C/P, D/P$, and prior 13–60 month returns. We form the deciles on past five-year sales growth (5-Yr SR) and market leverage (A/ME).

The $E/P, C/P$, and D/P Deciles

From Panel A of Table 7, the high-minus-low E/P portfolio is profitable from January 1972 to December 2005. This portfolio generates an average return of 0.68% per month (t-statistic = 2.81) and a CAPM alpha of 0.81% (t-statistic = 3.42). The alpha disappears in the Fama-French (1993) three-factor regression, which produces an insignificant intercept of −0.11% per month. The reason is that high E/P stocks have higher loadings on HML than low E/P stocks. Although its magnitude is higher than that from the Fama-French model, the neoclassical model also delivers an insignificant intercept of 0.31% per month (t-statistic = 1.31). The main driving force is that high E/P stocks have higher loadings on INV than low E/P stocks with the spread of 0.56 significant at the 1% level.

The C/P and D/P results are largely similar to those on the E/P portfolios. The high-minus-low C/P and D/P average returns are lower, 0.50% and 0.10% per month, respectively, and the latter is insignificant. But both strategies generate significant positive CAPM alphas, 0.64% and 0.45% per month. The Fama-French (1993) model reduces these alphas to insignificant levels because high C/P and D/P portfolios have significantly higher loadings on HML than low C/P and D/P loadings. The neoclassical model generates an insignificant alpha of 0.18% per month for the high-minus-low D/P portfolio (t-statistic = 0.76), but a marginally significant alpha of 0.48% per month for the high-minus-low C/P portfolio (t-statistic = 2.09). The driving force is that high C/P and D/P stocks have significantly higher loadings on INV than low C/P and D/P stocks.

The Long-Term Prior Returns and 5-Yr SR Deciles

Consistent with DeBondt and Thaler (1985), stocks with high prior 13–60 month returns (long-term winner) earn lower average returns than stocks with low prior 13–60 month returns (long-term losers). From Panel D of Table 7, the average-return spread is −0.41% per month, and that the long-term winner-minus-loser portfolio has a marginally significant alpha of −0.45%. The Fama and French (1993) model reduces the magnitude of the intercept to 0.24%. The long-term winners load negatively and long-term losers load positively on INV. As a result, the long-term winner-minus-loser has a negative INV-loading of −0.74, which goes in the right way in explaining its low average return. But the zero-investment portfolio has a significantly positive $PROD$-loading of 0.44, which goes in the wrong way in explaining its low average return. Overall, the neoclassical model produces an alpha of −0.41% per month (t-statistic = −1.58) for the zero-investment portfolio.

Consistent with Lakonishok, Shleifer, and Vishny (1994), stocks with high past five-year sales growth (5-Yr SR) earn lower average returns than stocks with low past five-year sales growth. The CAPM alpha of the high-minus-low 5-Yr SR portfolio is −0.55% per month (t-statistic = −2.53), although its average return of −0.35% is insignificant at the 5% level. The Fama-French (1993) model performs extremely well: The alpha of the zero-investment portfolio is only six basis points per month because of its large negative loading on HML. The zero-investment portfolio has an insignificant positive alpha of 0.28% per month in the neoclassical three-factor model. The driving force is a large negative INV-loading of −1.17 and a small negative $PROD$-loading of −0.27.

The Leverage Deciles

Bhandari (1988) and Fama and French (1992) report that stocks with high market leverage earn higher average returns than stocks with low market leverage. Following Fama and French, we measure market leverage, A/ME, as the ratio of the year-end book assets (COMPUSTAT annual item 6) to the year-end market equity. We also have constructed portfolios based on book leverage, the ratio of year-end book assets to year-end book equity. But the high-minus-low book-leverage portfolio has an insignificant average return and an insignificant CAPM alpha (not reported).

From Panel F of Table 7, high A/ME stocks earn higher average returns than low A/ME stocks, and the average-return spread of 0.57% per month is significant at the 5% level. The zero-cost high-minus-low A/M strategy generates a CAPM alpha of 0.65% (t-statistic = 2.62). The Fama-French (1993) model produces a negative alpha of -0.32% (t-statistic = -1.95). In the neoclassical model, high A/ME stocks have higher INV-loadings but slightly lower $PROD$-loadings than low A/ME stocks. As a result, the zero-cost portfolio has an insignificantly positive alpha of 0.35% per month.

5 Economic Fundamentals

To understand the driving forces of our regressions results, we turn to economic fundamentals for answers. In particular, we follow the empirical methodology of Fama and French (1995) and investigate how ROA and I/A vary across the testing portfolios, both in event-time and in calendar-time.

For the 25 size-BE/ME portfolios, we find that growth firms invest more than value firms, giving rise to the higher INV-loadings for value firms. Growth firms have experienced dramatic deteriorations in profitability in the past decade, giving rise to their lower $PROD$-loadings than value firms. Figure 2 reports more detailed evidence. From Panel A, consistent with Fama and French (1995), growth firms invest more than value firms for about four years before and five years after the portfolio formation year. Panels B and C show further that the growth firms invest more than value firms for almost every year from 1972 to 2005, regardless of the size of the firms. The panels plot the median I/As for the four extreme size-BE/ME portfolios. Untabulated results also show that growth portfolios have higher value-weighted I/As on average than value portfolios, where we value-weight the I/As across all the stocks in a given portfolio using their market equity as the weights. This evidence helps explain why value firms have high loadings than growth firms on the INV factor.

The story on ROA is more complicated. In the biggest size quintile, the median growth firm in the lowest BE/ME quintile has persistently higher ROAs than the median value firm in the highest BE/ME quintile for 11 years surrounding the portfolio formation and for almost every year from 1972 to 2005. In the smallest size quintile, the median growth firm only has slightly higher $ROAs$ than the median value firm for three years before and five years after the portfolio formation.

However, the event-time evidence masks dramatic calendar-time movements of the ROAs. Panel E of Figure Figure 2 reports a striking downward spike of ROA for the portfolio consisting of stocks in the smallest size and the lowest BE/ME quintiles in the past decade. The ROA starts at about 0.50% per quarter in 1997, drops rapidly to -4.50% in 2003, and then rises back to 0.50% in 2005. Similar but less dramatic downward spikes are visible for growth firms in the second, third, and fourth, but not in the biggest size quintiles. These spikes drive the mostly positive $PROD$-loadings for the value-minus-growth portfolios in Tables 3 and 4. Untabulated results verify that the value-minus-growth portfolios have negative $PROD$-loadings across all the five size quintiles in the sample from January 1972 to December 1995 before the downward ROA spikes occur.

Figure 3 provides detailed evidence for the 25 size-momentum portfolios. From Panel A, winners have higher ROA than losers for five quarters before and 20 quarters after the portfolio formation month. In calendar time, winners also have consistently higher ROA than losers, especially in smallest size quintile (Panels B and C). This evidence explains the higher $PROD$-loadings for the winners documented in Tables 3 and 4.

Panel D of Figure 3 shows that, although winners have higher I/As at the portfolio formation month t, they have lower I/As than losers from month $t-60$ to month $t-8$. Consistent with the event-time evidence, Panel E shows that winners have higher contemporaneous I/As than losers in calendar time in the smallest size quintile. The contemporaneous I/A is the current yearend I/A

value; for example, if the current month is March or September 2003, the contemporaneous I/A is the I/A at the end of year 2003. But more important, Panel F shows further that winners also have lower lagged (sorting-effective) I/As than losers in the smallest size quintile. The sorting-effective I/A is the I/A value on which an annual sort on I/A in each June (as in our construction of INV) is based. For example, if the current month is March 2003, then the sorting-effective I/A is the I/A at the fiscal yearend of 2001 because the annual sort on I/A is done in June 2002. If the current month is September 2003, the sorting-effective I/A is the I/A at the yearend of 2002 because the applicable sort on I/A is done in June 2003. Because INV is rebalanced annually, these lower sorting-effective I/As of winners explain their higher INV-loadings than losers.

Table 8 shows that ROA varies across the deciles sorted on distress measures and on earnings, and that I/A varies across various value deciles. Portfolio ROA and I/A are value-weighted across all stocks in the portfolio, where the weights are given by their market equity to be consistent with the calculations of portfolio returns. From Panel A, ROA decreases monotonically from the less distressed firms to more distress firms. The ROA of the high F-Prob decile is lower than the ROA of the low F-Prob decile by 5.88% per quarter (t-statistic = 14.72). Similarly, the ROA of the high O-score decile is lower than the ROA of the low O-score decile by 7.54% per quarter (t-statistic = 13.89). This evidence on ROA explains the higher $PROD$-loadings and thus higher average returns of less distressed firms than those of more distressed firms.

Panel A of Table 8 also shows that, not surprisingly, high ROA firms have a higher average ROA than low ROA firms. The ROA-spread of 11.67% per quarter (t-statistic = 20.84) goes a long way in generating a high $PROD$-loading spread and thus a high average-return spread between the two extreme ROA deciles. The ROA-spread between the two extreme SUE deciles is only 1.22% per quarter, albeit highly significant (t-statistic = 11.86). This lower ROA-spread explains why the neoclassical model is only partially successful in explaining the post-earnings-announcement drift.

The rest of Table 8 shows that I/A decreases with various valuation ratios including E/P, C/P, D/P, and A/ME, and increases with prior 13-60 month returns and past five-year sales growth, meaning again that value firms invest less and load more on INV than growth firms. For example, high E/P firms invest less than low E/P firms by 2.99% per quarter (t-statistic = 5.59). The I/A spread is higher across portfolios sorted on other value measures.

6 Interpretation, Applications, and Open Questions

We propose a new factor model that includes the market factor, the investment factor (low-minus-high investment-to-assets portfolio), and the productivity factor (high-minus-low earnings-to-assets portfolio). We motivate this factor structure through neoclassical reasoning. We document that the neoclassical three-factor model captures the anomalous average-return variations related to short-term prior returns, financial distress, and to some extent, earnings. The model also captures the relations of average returns with earnings-to-price, cash flow-to-price, book-to-market, market leverage, long-term past sales growth, and long-term prior returns. At a minimum, our evidence suggusts that the cross section of returns can largely be summarized by the neoclassical three-factor model.

6.1 Interpretation

Following Fama and French (1993, 1996), we interpret the investment and the productivity factors as common factors in the cross section of returns. While Fama and French pursue a more aggressive interpretation that their similarly constructed SMB and HML are risk factors in the context of ICAPM or APT, we are reluctant to take a strong stance on the risk interpretation of our factors.

On the one hand, the theoretical arguments we use to motivate the two factors are based on recent developments in equilibrium asset pricing theory, which does not assume any form of over- or underreaction. The crux is that, similar to the way in which aggregate expected returns covary with business cycles (e.g., Campbell and Cochrane 1999), expected returns in the cross section covary with firm characteristics, corporate policies, and events. The q-theory model allows and predicts these endogenous relations, but the CAPM and other factor models that have been used to control for expected returns in the empirical anomalies literature do not. Rejecting the CAPM and other traditional factor models thus does not automatically reject market efficiency because of the bad-model problem (e.g., Fama 1998).

Perhaps because of the lack of readily available proxies for investor sentiment, researchers often use valuation ratios to proxy for mispricing. Interpreting the Fama and French (1993) factors is thus somewhat difficult because size and book-to-market directly involve market equity. In contrast, the interpretation of our neoclassical factors is relatively clean because they are constructed on economic fundamentals, which are less likely to be affected by mispricing, at least directly.

On the other hand, investor sentiment can presumably affect investment policy and thus profitability through shareholder discount rates (e.g., Polk and Sapienza 2006). Managerial overconfidence can presumably distort corporate investment because overconfident managers tend to overestimate the returns to their investment projects (e.g., Malmendier and Tate 2005). Our tests below do not rule out these behavioral interpretations.

More important, risk-based and characteristics-based interpretations on any common factor are not mutually exclusive; in fact, they are the two sides of the same coin. Challenging the Fama and French (1993) risk-interpretation of their SMB and HML factors, Daniel and Titman (1997) argue that it is the size and book-to-market characteristics rather than the covariance structure of returns that explain the cross-sectional variations in stock returns. However, emerging from the q-theory framework is the central insight that characteristics are sufficient statistics of expected returns. The reason is that we can derive an analytical link between covariances and characteristics, as shown in equation (A.10) in Appendix A.

However, for the practical purposes of estimating expected returns, we believe that characteristics-based models are better equipped than covariances-based models. The reason is simple: In a time-varying, dynamic world, characteristics are more precisely measured than covariances. And a horse race often declares characteristics as the winner. This observation holds even in simulated data generated from dynamic single-factor models (see, for example, Gomes, Kogan, and Zhang 2003; Li, Livdan, and Zhang 2007). It is thus not inconceivable that the relative success of characteristics-based models results from measurement errors in covariances rather than systematic mispricing, especially given that the q-theory predicts the characteristics should covary with expected returns.

6.2 Applications

Our pragmatic approach means that, in principle, our neoclassical model can be used in many applications that require estimates of expected returns. Examples include portfolio choice, portfolio performance evaluation, measurement of abnormal returns in event studies, and the cost of capital estimates. These applications depend on the evidence that the neoclassical factors provide an adequate summary of the cross section of average returns. The motivation of our factors from equilibrium asset pricing theory also raises the confidence that the empirical performance of the neoclassical model is likely to persist in the future.

Regressing the excess returns of a target portfolio on the neoclassical factors can provide the exposures of the portfolio to the factors. The expected return estimate on the portfolio can be obtained by summing the products of the regression slopes and their historical average premiums for their corresponding factors. The estimate can then be used to guide portfolio choice and capital budgeting decisions. We can use a similar procedure to evaluate the performance of a managed portfolio. The intercept from regressing the excess return of the managed portfolio on the neoclassical factors is the estimated average abnormal return of the portfolio. This abnormal return can be used to judge whether the manager has done a good job in generating average returns greater than the average returns from the passive management of combining the neoclassical factors that we have identified.

The voluminous literatures in empirical corporate finance and capital markets research in accounting have used factor models to measure abnormal performance following corporate events. The intercepts from the market regression and the Fama-French (1993) three-factor regression are used to measure average abnormal returns. Our evidence suggests that the intercepts from the neoclassical three-factor regressions are likely to do a better job identifying abnormal performance.

For example, using the CAPM alpha as the measure of abnormal performance, Agrawal, Jaffe, and Mandelker (1992) document that stockholders of acquiring firms suffer a significant loss of about

10% over the five post-merger period. Because mergers and acquisitions are a form of capital investment from the perspective of acquires, we conjecture that the post-merger underperformance is a manifestation of the negative relation between investment-to-assets and expected returns. Using the neoclassical model is likely to yield more precise estimates of abnormal performance. For another example, Sloan (1996) documents that firms with high accounting accruals underperform firms with low accounting accruals in the three years after the portfolio formation. However, a major component of accruals is the investment on working capital. If working capital and other major inputs such as buildings, machinery, and equipment are complements in the production process of firms, then working capital investment and long-term capital investment should be positively correlated. We thus conjecture that the accrual anomaly is basically the negative investment-return relation in disguise, and that the neoclassical model can reduce the magnitude of the accrual anomaly.

6.3 Open Questions

We take the pragmatic approach in constructing common factors motivated from neoclassical economics. While useful in providing a parsimonious factor model for practical purposes, this approach leaves a more fundamental question unanswered. The neoclassical investment and productivity factors are constructed directly on firm characteristics. Although we show formally that these characteristics are related to risk, our investment-based approach does not characterize the nature or quantity the amount of underlying risk. The same critique applies to the structural estimation approach of Liu, Whited, and Zhang (2007). The underlying philosophy is that, instead of determining unobservable expected returns from equally unobservable risk as in traditional asset pricing literature, we infer unobservable expected returns from observable firm characteristics and corporate policies.

It is possible to link risk to some fundamental features of the real economy even in firm-centered partial equilibrium models. Johnson (2002) shows that the curvature of log price-dividend ratio with respect to expected growth is convex, meaning that the log price-dividend ratio is more sensitive to changes in expected growth when expected growth is high. Johnson argues that this expected-growth risk might drive momentum. Carlson, Fisher, and Giammarino (2004) relate the risk of value-minus-growth strategies to operating leverage. The high operating leverage of value firms relative to that of growth firms makes the cash flows of value firms covary more with economic downturns than the cash flows of growth firms. Zhang (2005) relate the risk of value firms to asymmetry in capital adjustment technology. The basic idea is that it is more costly for firms to downsize than to expand their productive capacity. Because value firms are less productive, they are stuck with more unproductive capital than growth firms in recessions. As a result, the cash flows of value firms again covary more with economic downturns than the cash flows of growth firms. Li, Livdan, and Zhang (2007) show that the same mechanism applies to the external financing technologies. However, based on specific models, these papers fall short of quantifying these risks in the data.

General equilibrium models, in which the consumer behavior and the firm behavior are jointly determined, hold the promise of understanding more fundamental driving forces of risk. However, because of their complex structures, constructing general equilibrium models that can be implemented empirically remains an important ongoing challenge.

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A A Two-Period q-Theory Model of Expected Returns

We derive the q-theory model of expected returns à la Cochrane (1991) using a two-period setup. For a more detailed exposition including the derivation and estimation in the infinite-period dynamic model, see Liu, Whited, and Zhang (2007).

Firms use capital and a vector of costlessly adjustable inputs to produce a perishable output good. Firms choose the levels of these inputs each period to maximize their operating profits, defined as revenues minus the expenditures on these inputs. Taking the operating profits as given, firms then choose optimal investment to maximize their market value.

There are only two periods, t and $t+1$. Firm j starts with capital stock k_{jt}, invests in period t, and produces in both t and $t+1$. The firm exits at the end of period $t+1$ with a liquidation value of $(1-\delta_j)k_{jt+1}$, in which δ_j is the firm-specific rate of capital depreciation. Operating profits, $\pi_{jt} = \pi(k_{jt}, x_{jt})$, depend upon capital, k_{jt}, and a vector of exogenous aggregate and firm-specific productivity shocks, denoted x_{jt}. Operating profits exhibit constant returns to scale, that is, $\pi(k_{jt}, x_{jt}) = \pi_1(k_{jt}, x_{jt})k_{jt}$, in which numerical subscripts denote partial derivatives. The expression $\pi_1(k_{jt}, x_{jt})$ is therefore the marginal product of capital.

The law of motion for capital is $k_{jt+1} = i_{jt} + (1-\delta_j)k_{jt}$, in which i_{jt} denotes capital investment. We use the one-period time-to-build convention: Capital goods invested today only become productive at the beginning of the next period. Investment incurs quadratic adjustment costs given by $(a/2)(i_{jt}/k_{jt})^2 k_{jt}$, in which $a > 0$ is a constant parameter. The adjustment-cost function is increasing and convex in i_{jt}, decreasing in k_{jt}, and exhibits constant returns to scale.

Let m_{t+1} be the stochastic discount factor from time t to $t+1$, which is correlated with the aggregate component of x_{jt+1}. Firm j chooses i_{jt} to maximize the market value of equity:

$$\underbrace{\max_{\{i_{jt}\}} \left\{ \overbrace{\pi(k_{jt}, x_{jt}) - i_{jt} - \frac{a}{2}\left(\frac{i_{jt}}{k_{jt}}\right)^2 k_{jt}}^{\textbf{Cash flow at period } t} + E_t\left[m_{t+1} \left[\overbrace{\pi(k_{jt+1}, x_{jt+1}) + (1-\delta_j)k_{jt+1}}^{\textbf{Cash flow at period } t+1} \right] \right] \right\}}_{\textbf{Cum dividend market value of equity at period } t}. \tag{A.1}$$

The first part of this expression, denoted by $\pi(k_{jt}, x_{jt}) - i_{jt} - (a/2)(i_{jt}/k_{jt})^2 k_{jt}$, is net cash flow during period t. Firms use operating profits $\pi(k_{jt}, x_{jt})$ to invest, which incurs both purchase costs, i_{jt}, and adjustment costs, $(a/2)\,(i_{jt}/\,k_{jt})^2\,k_{jt}$. The price of capital is normalized to be one. If net cash flow is positive, firms distribute it to shareholders, and if net cash flow is negative, firms collect external equity financing from shareholders. The second part of equation (A.1) contains the expected discounted value of cash flow during period $t+1$, which is given by the sum of operating profits and the liquidation value of the capital stock at the end of $t+1$.

Taking the partial derivative of equation (A.1) with respect to i_{jt} yields the first-order condition:

$$\overbrace{1 + a\left(\frac{i_{jt}}{k_{jt}}\right)}^{\textbf{Marginal cost of investment at period } t} \quad = \quad E_t\left[m_{t+1}\left[\overbrace{\pi_1(k_{jt+1}, x_{jt+1}) + (1-\delta_j)}^{\textbf{Marginal benefit of investment at period } t+1}\right]\right] \equiv q_{jt}. \tag{A.2}$$

The left side of the equality is the marginal cost of investment, and the right side is the marginal benefit commonly dubbed marginal q, denoted q_{jt}. To generate one additional unit of capital at the beginning of next period, k_{jt+1}, firms must pay the price of capital and the marginal adjustment cost, $a(i_{jt}/k_{jt})$. The next-period marginal benefit of this additional unit of capital includes the marginal product of capital, $\pi_1(k_{jt+1}, x_{jt+1})$, and the liquidation value of capital net of depreciation, $1-\delta_j$. Discounting this next-period benefit using the pricing kernel m_{t+1} yields the marginal q.

To derive asset pricing implications from this two-period q-theoretic model, we first define the investment return as the ratio of the marginal benefit of investment at period $t+1$ divided by the marginal cost of investment at period t:

$$\underbrace{r^I_{jt+1}}_{\textbf{Investment return from period } t \textbf{ to } t+1} \quad \equiv \quad \frac{\overbrace{\pi_1(k_{jt+1}, x_{jt+1}) + (1-\delta_j)}^{\textbf{Marginal benefit of investment at period } t+1}}{\underbrace{1 + a\,(i_{jt}/k_{jt})}_{\textbf{Marginal cost of investment at period } t}} \tag{A.3}$$

Following Cochrane (1991), we divide equation (A.2) by the marginal cost of investment:

$$E_t\left[m_{t+1} r^I_{jt+1}\right] = 1. \tag{A.4}$$

We now show that under constant returns to scale, stock returns equal investment returns.

From equation (A.1) we define the ex-dividend equity value at period t, denoted p_{jt}, as:

$$\underbrace{p_{jt}}_{\textbf{Ex dividend equity value at period } t} = E_t\left[m_{t+1}\left[\overbrace{\pi(k_{jt+1}, x_{jt+1}) + (1-\delta_j)k_{jt+1}}^{\textbf{Cash flow at period } t+1}\right]\right], \quad \text{(A.5)}$$

The ex-dividend equity value, p_{jt}, equals the cum-dividend equity value—the maximum in equation (A.1)—minus the net cash flow over period t. We can define the stock return, r^S_{jt+1}, as

$$\underbrace{r^S_{jt+1}}_{\textbf{Stock return from period } t \textbf{ to } t+1} = \frac{\overbrace{\pi(k_{jt+1}, x_{jt+1}) + (1-\delta_j)k_{jt+1}}^{\textbf{Cash flow at period } t+1}}{\underbrace{E_t[m_{t+1}[\pi(k_{jt+1}, x_{jt+1}) + (1-\delta_j)k_{jt+1}]]}_{\textbf{Ex dividend equity value at period } t}}, \quad \text{(A.6)}$$

in which the ex-dividend market value of equity in the numerator is zero in this two-period setting.

Dividing both the numerator and the denominator of equation (A.6) by k_{jt+1}, and invoking the constant returns assumption yields:

$$r^S_{jt+1} = \frac{\pi_1(k_{jt+1}, x_{jt+1}) + (1-\delta_j)}{E_t[m_{t+1}[\pi_1(k_{jt+1}, x_{jt+1}) + (1-\delta_j)]]} = \frac{\pi_1(k_{jt+1}, x_{jt+1}) + (1-\delta_j)}{1 + a(i_{jt}/k_{jt})} = r^I_{jt+1}.$$

The second equality follows from the first-order condition given by equation (A.2). Because of this equivalence, in what follows we use r_{jt+1} to denote both stock and investment returns.

The marginal product of capital in the numerator of the investment-return equation (A.3) is closely related to earnings, so expected returns increase with earnings. Specifically, earnings equals operating cash flows minus capital depreciation, which is the only accrual in our model. Let e_{jt} denote earnings, then:

$$\underbrace{e_{jt}}_{\textbf{Earnings}} \equiv \overbrace{\pi(k_{jt}, x_{jt})}^{\textbf{Operating cash flows}} - \underbrace{\delta_j k_{jt}}_{\textbf{Capital depreciation}}. \quad \text{(A.7)}$$

Using equation (A.7) to rewrite equation (A.3) yields:

$$\underbrace{E_t[r_{jt+1}]}_{\textbf{Expected return}} = \frac{\overbrace{E_t\left[\pi_{jt+1}/k_{jt+1}\right]}^{\textbf{Average product of capital}} + 1 - \delta_j}{\underbrace{1 + a(i_{jt}/k_{jt})}_{\textbf{Marginal cost of investment}}} = \frac{\overbrace{E_t[e_{jt+1}/k_{jt+1}]}^{\textbf{Expected profitability}} + 1}{\underbrace{1 + a(i_{jt}/k_{jt})}_{\textbf{Marginal cost of investment}}} \tag{A.8}$$

Given the market-to-book ratio in the denominator, equation (A.8) predicts that the expected return increases with the expected profitability. Haugen and Baker (1996) and Fama and French (2006) show that, controlling for market valuation ratios, firms with high expected profitability earn higher average returns than firms with low expected profitability. Further, the magnitude of the profitability-return relation equals $1/(1 + a(i_{jt}/k_{jt})) = k_{jt+1}/p_{jt}$, which is inversely related to market capitalization, p_{jt}.

As emphasized in Liu, Whited, and Zhang (2007), equation (A.8) expresses expected returns purely in terms of characteristics. In other words, characteristics are sufficient statistics of expected returns. To show that characteristics and covariances are the two sides of the same coin, we follow Cochrane (2005, p. 14–16) to rewrite equation (A.4) as the beta-pricing form:

$$E_t[r_{jt+1}] = r_{ft} + \beta_{jt}\lambda_{mt} \tag{A.9}$$

where r_{ft} is the risk-free rate, $\beta_{jt} \equiv -\mathrm{Cov}_t[r_{jt+1}, m_{t+1}]/\mathrm{Var}_t[m_{t+1}]$ is the amount of risk, and $\lambda_{mt} \equiv \mathrm{Var}_t[m_{t+1}]/E_t[m_{t+1}]$ is the price of risk. Combining equations (A.8) and (A.9) yields:

$$\beta_{jt} = \left(\frac{E_t[e_{jt+1}/k_{jt+1}] + 1}{1 + a(i_{jt}/k_{jt})} - r_{ft}\right)/\lambda_{mt} \tag{A.10}$$

which provides an analytical link between covariances and characteristics.

B The Distress Measures

We construct the failure probability measure or F-Prob following Campbell, Hilscher, and Szilagyi (2006, column three of Table 4):

$$\begin{aligned} F\text{–Prob}_t \equiv & -9.164 - 20.264\, NIMTAAVG_t + 1.416\, TLMTA_t - 7.129\, EXRETAVG_t \\ & + 1.411\, SIGMA_t - 0.045\, RSIZE_t - 2.132\, CASHMTA_t + 0.075\, MB_t - 0.058\, PRICE_t \quad \text{(B.1)} \end{aligned}$$

where

$$NIMTAAVG_{t-1,t-12} \equiv \frac{1-\phi^2}{1-\phi^{12}} \left(NIMTA_{t-1,t-3} + \cdots + \phi^9 NIMTA_{t-10,t-12} \right) \quad \text{(B.2)}$$

$$EXRETAVG_{t-1,t-12} \equiv \frac{1-\phi}{1-\phi^{12}} \left(EXRET_{t-1} + \cdots + \phi^{11} EXRET_{t-12} \right) \quad \text{(B.3)}$$

The coefficient $\phi = 2^{-1/3}$, meaning that the weight is halved each quarter. $NIMTA$ is net income (COMPUSTAT quarterly item 69) divided by the sum of market equity and total liabilities (item 54). The moving average $NIMTAAVG$ is designed to capture the idea that a long history of losses is a better predictor of bankruptcy than one large quarterly loss in a single month. $EXRET \equiv \log(1 + R_{it}) - \log(1 + R_{\text{S\&P500},t})$ is the monthly log excess return on each firm's equity relative to the S&P 500 index. The moving average $EXRETAVG$ is designed to capture the idea that a sustained decline in stock market value is a better predictor of bankruptcy than a sudden stock price decline in a single month. $TLMTA$ is the ratio of total liabilities divided by the sum of market equity and total liabilities. $SIGMA$ is the volatility of each firm's daily stock return over the past three months. $RSIZE$ is the relative size of each firm measured as the log ratio of its market equity to that of the S&P 500 index. $CASHMTA$, used to capture the liquidity position of the firm, is the ratio of cash and short term investments divided by the sum of market equity and total liabilities. MB is the market-to-book equity. $PRICE$ is the log price per share of the firm.

We follow Olson (1980, model one of Table 4) to construct O-score:

$$\begin{aligned} & -1.32 - 0.407\, \log(MKTASSET/CPI) + 6.03\, TLTA - 1.43\, WCTA + 0.076\, CLCA \\ & - 1.72\, OENEG - 2.37\, NITA - 1.83\, FUTL + 0.285\, INTWO - 0.521\, CHIN \quad \text{(B.4)} \end{aligned}$$

where $MKTASSET$ is market assets defined as book asset with book equity replaced by market equity. We calculate $MKTASSET$ as total liabilities + Market Equity + 0.1×(Market Equity − Book Equity), where total liabilities are given by COMPUSTAT quarterly item 54. The adjustment of $MKTASSET$ using ten percent of the difference between market equity and book equity follows Campbell, Hilscher, and Szilagyi (2007) to ensure that assets are not close to zero. The construction of book equity follows Fama and French (1993). CPI is the consumer price index. $TLTA$ is the leverage ratio defined as the book value of debt divided by $MKTASSET$. $WCTA$ is working capital divided by market assets, (COMPUSTAT quarterly item 40 − item 49)/$MKTASSET$. $CLCA$ is current liability (item 40) divided by current assets (item 49). $OENEG$ is one if total liabilities exceeds total assets and is zero otherwise. $NITA$ is net income (item 69) divided by assets, $MKTASSET$. $FUTL$ is the fund provided by operations (item 23) divided by liability (item 54). $INTWO$ is equal to one if net income (item 69) is negative for the last two years and zero otherwise. $CHIN$ is $(NI_t NI_{t-1})/(|NI_t| + |NI_{t-1}|)$, where NI_t is net income (item 69) for the most recent quarter.

Table 1 : Properties of The INV and $PROD$ Factors, 1/1972–12/2005, 408 Months

The Fama-French (1993) factors MKT, SMB, and HML as well as the momentum factor WML are from Kenneth French's Web site. INV is the zero-cost portfolio long in stocks with the lowest 30% investment-to-assets and short in stocks with the highest 30% investment-to-assets. $PROD$ is the zero-cost portfolio long in stocks with the highest 30% of earnings-to-assets and short in stocks with the lowest 30% of earnings-to-assets. To construct INV, we perform a double sort on size and investment-to-assets, I/A. I/A is the annual change in gross property, plant, and equipment (COMPUSTAT annual item 7) plus the annual change in inventories (item 3) divided by the lagged book value of assets (item 6). Changes in property, plant, and equipment measure capital investment in long-lived assets used in operations over many years such as buildings, machinery, furniture, and other equipment. Changes in inventories measure capital investment in short-lived assets used in a normal operating cycle such as merchandise, raw materials, supplies, and work in progress. In each June from 1972 to 2005, all NYSE stocks on CRSP are sorted on market equity (price times shares), and the median NYSE size is used to split NYSE, Amex, and NASDAQ stocks into two groups, small and big. We also break NYSE, Amex, and NASDAQ stocks into three investment-to-assets groups using the breakpoints for the low 30%, middle 40%, and high 30% of the ranked investment-to-assets for stocks traded on all three exchanges. From the intersections of the two size and the three investment-to-assets groups, we construct six size-I/A portfolios. Monthly value-weighted returns on the six portfolios are calculated from July of year t to June of year $t+1$, and the portfolios are rebalanced in June of year $t+1$. INV is the difference (low-minus-high investment), each month, between the simple average of the returns on the two low-I/A portfolios and the simple average of the returns on the two high-I/A portfolios. To construct $PROD$, we perform a double sort on size and earnings-to-assets, ROA. ROA is quarterly earnings (COMPUSTAT quarterly item 8) divided by one-quarter-lagged assets (item 44, plus the difference between market equity and book equity multiplied by 0.10). The adjustment of quarterly assets, borrowed from Campbell, Hilscher, and Szilagyi (2007), is meant to mitigate the impact of assets close to zero when used to calculate ROA. Each month from January 1972 to December 2005, we sort NYSE, Amex, and NASDAQ stocks into three groups based on the breakpoints for the low 30%, middle 40%, and the high 30% of the ranked quarterly ROA from at least four months ago for stocks traded on all three exchanges. We use the four-month lag to be sure that the accounting information is known before the portfolio formation. Also, in each June, we sort all NYSE stocks on size and use the NYSE median to split NYSE, Amex, and NASDAQ stocks into two groups, small and big. We form six portfolios from the intersections of the two size and the three ROA groups. Monthly value-weighted returns on the six portfolios are calculated for the current month, and the portfolios are rebalanced monthly. $PROD$ is the difference (high-minus-low productivity), each month, between the simple average of the returns on the two high-ROA portfolios and the simple average of the returns on the two low-ROA portfolios.

Panel A: Summary Statistics and Traditional Factor Regressions (t-Statistics in Parentheses)

	Mean	α	β_{MKT}	β_{SMB}	β_{HML}	β_{WML}	R^2
INV	0.45	0.53	−0.16				0.13
	(4.57)	(5.72)	(−7.93)				
		0.36	−0.09	0.05	0.25		0.25
		(4.12)	(−4.38)	(1.97)	(7.81)		
		0.25	−0.08	0.05	0.27	0.10	0.29
		(2.87)	(−3.75)	(2.00)	(8.75)	(5.05)	
$PROD$	0.73	0.81	−0.15				0.03
	(3.02)	(4.43)	(−3.83)				
		0.79	−0.06	−0.39	0.08		0.16
		(4.53)	(−1.32)	(−7.15)	(1.22)		
		0.52	−0.02	−0.39	0.14	0.25	0.23
		(3.03)	(−0.47)	(−7.53)	(2.29)	(6.42)	

Panel B: Correlation Matrix (*, **: Significant at 5% and 1% Levels, Respectively)

	$PROD$	MKT	SMB	HML	WML
INV	0.04	$-0.37^{\star\star}$	$-0.08^{\star}$	$0.46^{\star\star}$	$0.18^{\star\star}$
$PROD$		$-0.19^{\star\star}$	$-0.38^{\star\star}$	$0.19^{\star\star}$	$0.27^{\star\star}$
MKT			$0.26^{\star\star}$	$-0.45^{\star\star}$	−0.07
SMB				$-0.29^{\star\star}$	−0.02
HML					$-0.11^{\star}$

Table 2 : Summary Statistics and Traditional Factor Regressions for Monthly Percent Excess Returns on 25 Portfolios Formed on Size and Book-to-Market Equity (BE/ME) and on 25 Portfolios Formed on Size and Prior 2–12 Month Returns (Momentum), 1/1972–12/2005, 408 Months

R_f is the one-month Treasury bill rate observed at the beginning of the month. The data for R_f, the Fama-French (1993) factors (MKT, SMB, and HML) are from Kenneth French's Web site. The 25 size-BE/ME portfolios and the 25 size-momentum portfolios are also from Kenneth French's Web site.

Panel A: 25 Portfolios Formed on Size and BE/ME

	Low	2	3	4	High	H-L	Low	2	3	4	High	H-L	Low	2	3	4	High	H-L
	Summary Statistics and Market Regressions: $R_j - R_f = \alpha_j + \beta_j\, MKT + \varepsilon_j$																	
	Mean						Standard Deviations						R^2					
Small	0.09	0.80	0.88	1.07	1.17	1.08	8.27	7.00	5.87	5.47	5.84	4.45	0.62	0.60	0.63	0.61	0.58	0.21
2	0.34	0.65	0.88	0.98	1.03	0.69	7.58	6.03	5.30	5.08	5.72	4.39	0.74	0.74	0.73	0.69	0.64	0.19
3	0.41	0.72	0.74	0.84	1.07	0.66	6.94	5.50	4.86	4.74	5.38	4.78	0.78	0.81	0.76	0.71	0.65	0.14
4	0.51	0.57	0.79	0.84	0.91	0.40	6.29	5.27	4.97	4.67	5.23	4.52	0.85	0.85	0.78	0.74	0.67	0.11
Big	0.40	0.60	0.57	0.63	0.61	0.21	4.97	4.73	4.46	4.31	4.81	4.29	0.87	0.86	0.77	0.66	0.55	0.06
	α						$t(\alpha)$						β					
Small	−0.62	0.22	0.38	0.61	0.69	1.30	−2.50	1.02	2.15	3.60	3.68	6.81	1.43	1.19	1.02	0.94	0.98	−0.45
2	−0.36	0.09	0.40	0.53	0.53	0.90	−1.93	0.59	2.85	3.70	3.15	4.65	1.43	1.14	0.99	0.92	1.01	−0.42
3	−0.25	0.18	0.28	0.41	0.60	0.85	−1.59	1.54	2.36	3.16	3.70	3.84	1.34	1.09	0.93	0.87	0.95	−0.40
4	−0.12	0.05	0.32	0.41	0.45	0.56	−0.97	0.44	2.75	3.41	2.98	2.67	1.27	1.07	0.97	0.88	0.94	−0.33
Big	−0.10	0.13	0.15	0.26	0.23	0.33	−1.10	1.43	1.42	2.06	1.43	1.59	1.02	0.96	0.86	0.77	0.78	−0.23
	Fama-French Three-Factor Regressions: $R_j - R_f = a_j + b_j\, MKT + s_j\, SMB + h_j\, HML + \varepsilon_j$																	
	a						$t(a)$						R^2					
Small	−0.52	0.07	0.09	0.23	0.15	0.68	−4.42	0.82	1.41	3.36	2.05	5.40	0.92	0.94	0.95	0.94	0.94	0.71
2	−0.21	−0.11	0.04	0.09	−0.05	0.16	−2.55	−1.51	0.60	1.24	−0.73	1.49	0.95	0.94	0.93	0.93	0.94	0.78
3	−0.03	−0.03	−0.10	−0.07	0.00	0.03	−0.35	−0.39	−1.30	−0.90	0.01	0.26	0.95	0.90	0.90	0.89	0.88	0.79
4	0.12	−0.16	−0.05	−0.02	−0.10	−0.22	1.38	−1.75	−0.58	−0.27	−0.95	−1.78	0.94	0.89	0.88	0.88	0.86	0.77
Big	0.18	0.04	−0.03	−0.13	−0.27	−0.45	2.82	0.56	−0.31	−1.68	−2.35	−3.37	0.94	0.89	0.85	0.88	0.78	0.62
	b						s						h					
Small	1.08	0.96	0.91	0.89	0.99	−0.09	1.33	1.30	1.07	0.99	1.05	−0.27	−0.34	0.04	0.29	0.44	0.68	1.03
2	1.13	1.04	0.99	0.97	1.09	−0.04	0.98	0.86	0.73	0.71	0.85	−0.13	−0.39	0.19	0.45	0.58	0.79	1.18
3	1.06	1.08	1.02	1.01	1.12	0.05	0.73	0.51	0.41	0.38	0.51	−0.22	−0.46	0.27	0.54	0.69	0.86	1.33
4	1.07	1.11	1.10	1.04	1.16	0.10	0.40	0.22	0.18	0.19	0.19	−0.21	−0.42	0.29	0.55	0.64	0.83	1.26
Big	0.95	1.05	1.00	1.00	1.05	0.10	−0.29	−0.22	−0.23	−0.21	−0.12	0.17	−0.39	0.16	0.31	0.63	0.80	1.19

Panel B: 25 Portfolios Formed on Size and Momentum

	Loser	2	3	4	Winner	W-L	Loser	2	3	4	Winner	W-L	Loser	2	3	4	Winner	W-L
	Summary Statistics and Market Regressions: $R_j - R_f = \alpha_j + \beta_j\,MKT + \varepsilon_j$																	
	Mean						Standard Deviations						R^2					
Small	−1.57	−0.75	−0.47	−0.37	−0.57	1.00	7.81	6.02	5.65	5.83	6.77	3.97	0.58	0.61	0.61	0.64	0.65	0.01
2	−0.38	−0.06	0.09	0.31	0.37	0.75	7.59	5.97	5.48	5.58	6.83	4.53	0.70	0.70	0.72	0.72	0.72	0.01
3	0.09	0.11	0.25	0.45	0.89	0.81	7.27	5.57	5.13	5.11	6.42	5.39	0.68	0.76	0.77	0.78	0.73	0.01
4	0.32	0.23	0.29	0.46	0.90	0.59	7.23	5.49	4.97	4.81	5.99	6.05	0.64	0.74	0.79	0.83	0.74	0.01
Big	0.53	0.65	0.49	0.72	1.12	0.64	6.88	4.85	4.32	4.41	5.52	6.62	0.52	0.66	0.76	0.77	0.70	0.00
	α						$t(\alpha)$						β					
Small	−2.21	−1.26	−0.95	−0.87	−1.16	1.06	−9.20	−6.94	−5.51	−4.99	−5.73	5.49	1.31	1.03	0.97	1.02	1.19	−0.11
2	−1.06	−0.60	−0.41	−0.21	−0.25	0.81	−5.39	−3.85	−2.90	−1.41	−1.40	3.69	1.39	1.10	1.02	1.04	1.27	−0.12
3	−0.56	−0.41	−0.24	−0.04	0.30	0.86	−2.81	−3.06	−1.95	−0.36	1.80	3.24	1.31	1.07	0.99	0.99	1.20	−0.11
4	−0.33	−0.28	−0.18	−0.02	0.34	0.66	−1.47	−2.01	−1.58	−0.15	2.25	2.17	1.27	1.03	0.97	0.96	1.13	−0.13
Big	−0.07	0.22	0.08	0.30	0.62	0.69	−0.29	1.57	0.77	2.83	4.16	2.09	1.09	0.87	0.83	0.85	1.01	−0.08
	Fama-French Three-Factor Regressions: $R_j - R_f = a_j + b_j\,MKT + s_j\,SMB + h_j\,HML + \varepsilon_j$																	
	a						$t(a)$						R^2					
Small	−2.52	−1.65	−1.34	−1.18	−1.33	1.19	−13.42	−13.32	−12.16	−11.15	−10.61	5.86	0.80	0.86	0.88	0.87	0.87	0.03
2	−1.27	−0.95	−0.73	−0.49	−0.31	0.96	−7.09	−7.56	−7.02	−4.65	−2.80	4.10	0.81	0.86	0.88	0.89	0.90	0.03
3	−0.70	−0.67	−0.53	−0.30	0.28	0.98	−3.41	−5.30	−5.42	−3.02	2.27	3.48	0.73	0.84	0.87	0.88	0.86	0.03
4	−0.43	−0.53	−0.47	−0.22	0.38	0.80	−1.73	−3.47	−4.55	−2.23	2.84	2.42	0.65	0.78	0.84	0.86	0.81	0.03
Big	−0.06	0.15	0.07	0.27	0.77	0.82	−0.21	1.02	0.65	2.71	5.14	2.24	0.52	0.68	0.79	0.80	0.71	0.01
	b						s						h					
Small	1.19	1.01	0.95	0.96	1.04	−0.15	1.16	0.94	0.91	0.90	1.03	−0.13	0.31	0.48	0.49	0.36	0.12	−0.19
2	1.30	1.09	1.02	1.01	1.09	−0.21	0.82	0.73	0.67	0.70	0.89	0.08	0.20	0.43	0.40	0.34	−0.04	−0.24
3	1.26	1.09	1.03	1.01	1.05	−0.21	0.53	0.44	0.45	0.45	0.69	0.17	0.14	0.34	0.40	0.33	−0.08	−0.22
4	1.26	1.11	1.07	1.02	1.01	−0.24	0.27	0.20	0.15	0.17	0.44	0.17	0.13	0.36	0.42	0.29	−0.12	−0.25
Big	1.12	0.94	0.89	0.92	0.95	−0.17	−0.13	−0.16	−0.24	−0.23	−0.01	0.13	0.00	0.13	0.06	0.08	−0.23	−0.23

Table 3 : Neoclassical Factor Regressions for Monthly Percent Excess Returns on 25 Portfolios Formed on Size and BE/ME and on 25 Portfolios Formed on Size and Prior 2–12 Month Returns (Momentum), 1/1972–12/2005, 408 Months

R_f is the one-month Treasury bill rate observed at the beginning of the month. The data for R_f and the market factor (MKT) are from Kenneth French's Web site. The 25 size-BE/ME portfolios and the 25 size-momentum portfolios are also from Kenneth French's Web site. See the caption of Table 1 for the description of the investment factor INV and the productivity factor $PROD$.

Panel A: 25 Portfolios Formed on Size and BE/ME

Neoclassical Factor Regressions: $R_j - R_f = a_j + b_j\, MKT + i_j\, INV + p_j\, PROD + \varepsilon_j$

	Low	2	3	4	High	H-L	Low	2	3	4	High	H-L	Low	2	3	4	High	H-L
	a						$t(a)$						R^2					
Small	−0.05	0.57	0.47	0.61	0.66	0.71	−0.19	2.31	2.32	3.23	3.32	3.46	0.70	0.66	0.66	0.64	0.62	0.36
2	0.10	0.19	0.33	0.46	0.42	0.32	0.47	1.15	2.22	3.08	2.36	1.58	0.77	0.75	0.73	0.69	0.67	0.32
3	0.15	0.19	0.13	0.23	0.39	0.25	0.85	1.45	1.05	1.74	2.27	1.09	0.80	0.81	0.77	0.72	0.66	0.26
4	0.15	−0.06	0.13	0.23	0.16	0.00	1.03	−0.59	1.13	1.93	0.97	0.02	0.86	0.86	0.79	0.75	0.70	0.22
Big	−0.09	−0.08	0.00	0.04	0.05	0.14	−0.96	−0.93	−0.03	0.29	0.31	0.65	0.89	0.88	0.78	0.68	0.56	0.12
	b						i						p					
Small	1.32	1.13	1.02	0.96	1.01	−0.31	−0.09	0.09	0.24	0.34	0.42	0.52	−0.64	−0.49	−0.27	−0.22	−0.24	0.40
2	1.32	1.12	1.01	0.95	1.05	−0.27	−0.37	0.01	0.19	0.20	0.40	0.77	−0.33	−0.13	−0.04	−0.04	−0.12	0.22
3	1.25	1.09	0.97	0.92	1.01	−0.23	−0.39	−0.02	0.18	0.23	0.37	0.77	−0.24	0.01	0.07	0.07	0.01	0.25
4	1.20	1.09	1.01	0.93	1.02	−0.18	−0.29	0.04	0.18	0.30	0.41	0.69	−0.14	0.11	0.11	0.03	0.10	0.24
Big	1.00	1.00	0.89	0.82	0.83	−0.17	−0.2	0.08	0.09	0.17	0.32	0.52	0.12	0.20	0.13	0.16	0.01	−0.11
	$t(b)$						$t(i)$						$t(p)$					
Small	20.88	18.16	18.37	17.11	16.39	−6.28	−0.69	0.78	2.42	3.42	3.84	4.20	−5.55	−4.17	−2.96	−2.83	−3.27	4.25
2	27.09	24.04	21.09	20.36	18.60	−4.95	−3.56	0.07	2.49	2.41	3.98	6.70	−3.83	−1.93	−0.72	−0.66	−1.64	2.54
3	32.37	28.22	25.06	24.41	19.86	−4.23	−4.25	−0.28	2.54	2.99	3.39	6.26	−3.06	0.16	1.42	1.08	0.15	2.04
4	40.65	34.92	30.14	28.15	23.07	−3.06	−4.52	0.61	2.65	4.17	4.44	5.84	−2.15	2.43	1.84	0.49	1.30	2.04
Big	37.62	45.40	34.35	23.49	18.85	−2.77	−4.23	1.61	1.23	2.31	2.82	3.90	4.40	5.59	2.66	2.43	0.12	−1.18

Panel B: 25 Portfolios Formed on Size and Momentum

Neoclassical Factor Regressions: $R_j - R_f = a_j + b_j\, MKT + i_j\, INV + p_j\, PROD + \varepsilon_j$

	Loser	2	3	4	Winner	W-L	Loser	2	3	4	Winner	W-L	Loser	2	3	4	Winner	W-L
	a						$t(a)$						R^2					
Small	−1.53	−1.10	−0.85	−0.80	−0.99	0.55	−6.10	−5.39	−4.39	−4.22	−4.56	2.53	0.69	0.64	0.63	0.65	0.67	0.18
2	−0.50	−0.46	−0.44	−0.22	−0.11	0.39	−2.35	−2.59	−2.78	−1.36	−0.55	1.53	0.76	0.71	0.72	0.72	0.73	0.08
3	−0.01	−0.34	−0.29	−0.13	0.30	0.31	−0.04	−2.19	−2.19	−0.99	1.63	1.04	0.73	0.76	0.77	0.79	0.73	0.09
4	0.28	−0.18	−0.30	−0.18	0.31	0.01	1.10	−1.10	−2.36	−1.78	1.75	0.04	0.69	0.74	0.80	0.84	0.74	0.10
Big	0.38	0.23	0.00	0.03	0.46	0.06	1.29	1.40	0.01	0.26	2.78	0.14	0.54	0.67	0.77	0.81	0.71	0.06
	b						i						p					
Small	1.17	1.01	0.96	1.02	1.17	0.00	−0.24	0.14	0.12	0.17	0.09	0.33	−0.69	−0.28	−0.20	−0.20	−0.27	0.41
2	1.26	1.07	1.03	1.05	1.25	−0.02	−0.34	−0.04	0.10	0.10	0.02	0.36	−0.48	−0.15	−0.02	−0.05	−0.19	0.28
3	1.18	1.05	1.00	1.01	1.21	0.02	−0.44	−0.10	0.04	0.05	0.02	0.47	−0.40	−0.03	0.04	0.08	−0.02	0.38
4	1.12	1.01	0.99	1.00	1.14	0.02	−0.51	−0.14	0.01	0.09	0.01	0.52	−0.42	−0.03	0.14	0.15	0.04	0.46
Big	0.98	0.86	0.84	0.91	1.06	0.08	−0.49	−0.09	−0.03	0.14	0.16	0.65	−0.23	0.05	0.12	0.24	0.11	0.34
	$t(b)$						$t(i)$						$t(p)$					
Small	18.67	16.61	15.79	16.95	18.28	0.03	−1.85	1.21	1.14	1.62	0.76	3.26	−7.75	−3.72	−2.92	−3.43	−3.81	4.34
2	25.11	21.43	21.06	20.91	23.12	−0.33	−2.85	−0.35	1.15	1.19	0.18	2.79	−5.71	−2.16	−0.45	−0.86	−2.68	2.23
3	21.12	24.33	23.75	22.94	25.53	0.30	−3.64	−1.08	0.55	0.60	0.26	3.21	−4.31	−0.47	0.71	1.66	−0.25	2.51
4	14.07	20.66	29.11	33.30	27.18	0.20	−3.69	−1.51	0.19	1.62	0.11	2.94	−4.04	−0.45	2.57	3.69	0.42	2.70
Big	11.80	15.92	28.37	37.87	27.07	0.82	−3.15	−1.00	−0.51	2.42	1.92	3.24	−2.37	0.83	2.53	6.54	1.55	2.26

Table 4 : Alternative Two-Factor Specifications of Neoclassical Regressions for Monthly Percent Excess Returns on 25 Portfolios Formed on Size and BE/ME and on 25 Portfolios Formed on Size and Prior 2–12 Month Returns, 1/1972–12/2005, 408 Months

R_f is the one-month Treasury bill rate observed at the beginning of the month. The data for R_f and the market factor (MKT) are from Kenneth French's Web site. The 25 size-BE/ME portfolios and the 25 size-momentum portfolios are also from Kenneth French's Web site. See the caption of Table 1 for the description of the investment factor INV and the productivity factor $PROD$.

Panel A: 25 Portfolios Formed on Size and BE/ME

Alternative Specification I: $R_j - R_f = a_j + b_j\, MKT + i_j\, INV + \varepsilon_j$

	Low	2	3	4	High	H-L	Low	2	3	4	High	H-L	Low	2	3	4	High	H-L
	a						b						i					
Small	−0.59	0.16	0.24	0.42	0.46	1.04	1.42	1.20	1.06	0.99	1.04	−0.37	−0.06	0.12	0.25	0.35	0.44	0.50
2	−0.18	0.08	0.29	0.42	0.32	0.50	1.38	1.14	1.02	0.96	1.07	−0.30	−0.35	0.01	0.19	0.20	0.41	0.76
3	−0.05	0.20	0.19	0.29	0.40	0.46	1.28	1.09	0.96	0.91	1.01	−0.28	−0.38	−0.02	0.17	0.23	0.37	0.75
4	0.03	0.03	0.23	0.25	0.24	0.21	1.23	1.07	0.99	0.93	1.01	−0.22	−0.28	0.03	0.17	0.30	0.40	0.68
Big	0.01	0.09	0.11	0.17	0.06	0.05	0.98	0.97	0.87	0.79	0.83	−0.15	−0.21	0.07	0.08	0.16	0.32	0.53
	$t(a)$						$t(b)$						$t(i)$					
Small	−2.29	0.71	1.34	2.47	2.45	5.52	21.91	19.44	19.45	17.84	17.01	−6.52	−0.41	0.90	2.45	3.36	3.77	4.10
2	−0.91	0.52	2.04	2.98	1.88	2.68	29.55	24.95	21.50	19.85	18.46	−5.27	−3.17	0.15	2.51	2.43	3.94	6.70
3	−0.33	1.57	1.58	2.21	2.48	2.15	35.16	28.28	24.22	22.19	18.80	−4.49	−3.82	−0.28	2.51	3.01	3.44	6.42
4	0.26	0.28	1.93	2.15	1.55	0.99	40.15	32.82	26.96	24.91	20.55	−3.35	−4.21	0.51	2.59	4.24	4.48	5.78
Big	0.16	1.02	0.97	1.38	0.37	0.23	38.59	39.65	31.82	20.73	17.67	−2.42	−4.30	1.17	1.06	2.18	2.81	4.00

Alternative Specification II: $R_j - R_f = a_j + b_j\, MKT + p_j\, PROD + \varepsilon_j$

	Low	2	3	4	High	H-L	Low	2	3	4	High	H-L	Low	2	3	4	High	H-L
	a						b						p					
Small	−0.10	0.62	0.60	0.79	0.89	0.99	1.33	1.11	0.98	0.90	0.94	−0.39	−0.64	−0.49	−0.27	−0.22	−0.25	0.39
2	−0.10	0.20	0.43	0.56	0.63	0.73	1.38	1.12	0.98	0.92	0.99	−0.39	−0.33	−0.13	−0.05	−0.04	−0.12	0.20
3	−0.06	0.18	0.22	0.36	0.60	0.66	1.31	1.09	0.94	0.88	0.95	−0.36	−0.23	0.01	0.07	0.06	0.01	0.24
4	0.00	−0.04	0.23	0.39	0.38	0.38	1.25	1.08	0.98	0.88	0.96	−0.29	−0.14	0.11	0.11	0.03	0.09	0.23
Big	−0.20	−0.04	0.04	0.13	0.22	0.42	1.04	0.99	0.88	0.79	0.78	−0.25	0.13	0.20	0.13	0.16	0.01	−0.12
	$t(a)$						$t(b)$						$t(p)$					
Small	−0.39	2.58	3.05	4.24	4.47	4.80	23.27	18.88	18.08	16.28	15.55	−8.15	−5.58	−4.17	−2.95	−2.81	−3.27	4.25
2	−0.49	1.22	3.04	3.82	3.64	3.58	30.81	24.27	20.34	19.99	17.52	−7.14	−3.80	−1.94	−0.76	−0.71	−1.71	2.42
3	−0.37	1.43	1.87	2.72	3.61	2.89	36.43	29.44	23.43	22.85	18.30	−6.01	−2.98	0.17	1.36	1.03	0.08	1.97
4	−0.02	−0.45	1.99	3.30	2.40	1.56	44.92	34.08	27.49	25.35	20.40	−4.80	−2.07	2.42	1.80	0.43	1.23	1.95
Big	−2.22	−0.40	0.39	0.96	1.30	1.93	39.66	48.30	31.39	23.63	18.53	−4.27	4.37	5.57	2.65	2.41	0.07	−1.25

Panel B: 25 Portfolios Formed on Size and Momentum

	Loser	2	3	4	Winner	W-L	Loser	2	3	4	Winner	W-L	Loser	2	3	4	Winner	W-L
	Alternative Specification I: $R_j - R_f = a_j + b_j\, MKT + i_j\, INV + \varepsilon_j$																	
	a						b						i					
Small	−2.11	−1.33	−1.01	−0.97	−1.21	0.89	1.28	1.06	0.99	1.05	1.21	−0.07	−0.20	0.15	0.13	0.18	0.11	0.31
2	−0.90	−0.59	−0.46	−0.26	−0.27	0.63	1.34	1.09	1.04	1.06	1.28	−0.06	−0.32	−0.03	0.10	0.11	0.03	0.35
3	−0.34	−0.36	−0.26	−0.06	0.29	0.63	1.25	1.05	1.00	1.00	1.21	−0.04	−0.42	−0.10	0.04	0.04	0.03	0.44
4	−0.07	−0.21	−0.19	−0.06	0.34	0.40	1.19	1.01	0.97	0.97	1.13	−0.05	−0.48	−0.14	0.00	0.08	0.01	0.49
Big	0.18	0.27	0.10	0.23	0.54	0.35	1.02	0.85	0.82	0.87	1.04	0.02	−0.48	−0.09	−0.04	0.13	0.15	0.63
	$t(a)$						$t(b)$						$t(i)$					
Small	−8.36	−7.12	−5.73	−5.46	−5.72	4.34	17.97	16.80	16.08	18.14	19.24	−1.13	−1.33	1.31	1.20	1.67	0.87	2.65
2	−4.12	−3.53	−3.21	−1.71	−1.42	2.55	23.82	20.49	20.76	21.16	23.74	−1.01	−2.18	−0.26	1.17	1.21	0.28	2.43
3	−1.56	−2.49	−2.03	−0.52	1.66	2.18	21.16	24.71	22.78	22.38	26.16	−0.49	−2.96	−1.05	0.53	0.56	0.27	2.75
4	−0.29	−1.36	−1.55	−0.57	2.12	1.20	14.11	20.68	26.16	30.63	26.46	−0.49	−2.97	−1.47	0.08	1.45	0.08	2.43
Big	0.67	1.76	0.94	2.14	3.49	0.98	11.98	15.96	28.09	29.87	24.56	0.21	−2.98	−1.03	−0.60	1.93	1.81	3.02
	Alternative Specification II: $R_j - R_f = a_j + b_j\, MKT + p_j\, PROD + \varepsilon_j$																	
	a						b						p					
Small	−1.66	−1.03	−0.79	−0.70	−0.94	0.73	1.20	0.99	0.94	0.99	1.15	−0.05	−0.68	−0.28	−0.20	−0.20	−0.27	0.41
2	−0.68	−0.48	−0.39	−0.17	−0.10	0.59	1.32	1.07	1.02	1.03	1.24	−0.08	−0.47	−0.15	−0.03	−0.05	−0.20	0.28
3	−0.24	−0.39	−0.27	−0.11	0.32	0.56	1.25	1.06	1.00	1.00	1.20	−0.05	−0.39	−0.03	0.04	0.08	−0.02	0.37
4	0.01	−0.26	−0.29	−0.14	0.31	0.30	1.20	1.03	0.99	0.98	1.14	−0.06	−0.41	−0.03	0.14	0.15	0.04	0.45
Big	0.12	0.18	−0.02	0.10	0.54	0.41	1.06	0.88	0.84	0.88	1.03	−0.02	−0.22	0.05	0.12	0.24	0.10	0.33
	$t(a)$						$t(b)$						$t(p)$					
Small	−6.77	−5.20	−4.22	−3.83	−4.58	3.43	19.61	16.19	15.81	17.24	19.75	−1.04	−7.69	−3.74	−2.97	−3.49	−3.81	4.20
2	−3.40	−2.82	−2.52	−1.07	−0.52	2.43	26.02	21.26	20.50	21.05	24.97	−1.38	−5.51	−2.15	−0.47	−0.89	−2.68	2.14
3	−1.18	−2.66	−2.11	−0.85	1.75	1.93	22.04	24.37	23.53	23.16	28.25	−0.72	−4.13	−0.45	0.71	1.65	−0.25	2.42
4	0.03	−1.68	−2.41	−1.35	1.88	0.87	15.20	21.15	29.40	33.08	29.21	−0.63	−3.82	−0.42	2.57	3.70	0.42	2.62
Big	0.43	1.17	−0.13	1.08	3.39	1.08	12.58	16.23	30.74	38.65	29.39	−0.20	−2.21	0.85	2.55	6.51	1.52	2.16

Table 5 : Summary Statistics and Factor Regressions for Monthly Percent Excess Returns on Deciles Formed on Campbell-Hilscher-Szilagyi's (2007) Failure Probability Measure (F-Prob) and Deciles Formed on Ohlson's (1980) O-Score, 1/1972–12/2005, 408 Months

R_f is the one-month Treasury bill rate observed at the beginning of the month. The data on R_f, the Fama-French (1993) three factors are from Kenneth French's Web site. See the caption of Table 1 for the description of the investment factor INV and the productivity factor $PROD$. F-Prob and O-score are defined in Appendix B. In June of each year t, we sort all NYSE, Amex, and NASDAQ stocks into ten deciles based on the breakpoints of F-Prob and O-score measured at the fiscal yearend of $t-1$ for the stocks traded on all three exchanges. Monthly value-weighted returns on the ten portfolios are calculated from July of year t to June of year $t+1$.

	Low	2	3	4	5	6	7	8	9	High	H-L
	Panel A: F-Prob Deciles										
Mean	0.44	0.31	−0.01	0.01	−0.06	−0.02	0.01	0.07	0.05	−0.01	−0.45
Std	5.52	4.59	4.60	4.68	5.00	5.38	6.22	7.35	7.93	9.77	7.61
α	−0.17	−0.26	−0.58	−0.56	−0.65	−0.65	−0.68	−0.75	−0.81	−0.95	−0.77
β	1.03	0.97	0.95	0.97	1.01	1.07	1.16	1.37	1.45	1.59	0.56
$t(\alpha)$	−1.14	−2.97	−6.01	−5.88	−5.33	−4.91	−3.67	−3.42	−3.47	−2.75	−2.10
a	−0.24	−0.20	−0.53	−0.58	−0.65	−0.66	−0.62	−0.82	−1.10	−1.12	−0.88
b	1.06	0.96	0.96	1.01	1.02	1.07	1.11	1.30	1.42	1.41	0.35
s	0.05	−0.12	−0.12	−0.12	−0.06	0.01	0.05	0.46	0.72	1.07	1.03
h	0.09	−0.07	−0.04	0.06	0.01	0.00	−0.10	0.00	0.27	−0.02	−0.11
$t(a)$	−1.52	−2.21	−5.56	−5.95	−5.15	−4.46	−3.28	−3.82	−4.90	−3.43	−2.51
a	−0.29	−0.33	−0.66	−0.52	−0.57	−0.36	−0.19	0.09	−0.14	0.08	0.36
b	1.06	0.98	0.97	0.96	0.99	1.00	1.03	1.17	1.29	1.35	0.29
i	0.00	−0.08	−0.04	−0.09	−0.05	−0.20	−0.30	−0.47	−0.06	−0.03	−0.03
p	0.13	0.13	0.12	0.00	−0.06	−0.21	−0.38	−0.68	−0.74	−1.17	−1.30
$t(a)$	−1.84	−3.58	−6.75	−4.50	−4.48	−2.56	−1.13	0.45	−0.63	0.23	1.09
$t(b)$	17.08	39.76	39.90	28.92	29.89	27.88	21.02	29.01	20.41	19.50	3.64
$t(i)$	0.01	−1.28	−0.81	−1.56	−0.63	−2.30	−2.68	−3.36	−0.41	−0.17	−0.16
$t(p)$	3.07	4.43	3.30	0.05	−1.01	−3.88	−6.14	−8.89	−8.25	−9.45	−10.69
	Panel B: O-Score Deciles										
Mean	−0.02	0.10	0.02	0.02	0.03	0.00	−0.06	−0.17	−0.14	−0.82	−0.80
Std	4.92	5.12	5.12	4.90	5.24	4.97	5.35	5.80	6.65	8.66	6.71
α	−0.52	−0.42	−0.49	−0.46	−0.47	−0.47	−0.54	−0.69	−0.71	−1.47	−0.95
β	1.03	1.06	1.04	0.98	1.01	0.95	0.98	1.04	1.16	1.33	0.30
$t(\alpha)$	−6.79	−4.98	−4.71	−4.54	−3.92	−3.80	−3.77	−4.18	−3.65	−4.97	−3.00
a	−0.37	−0.42	−0.66	−0.70	−0.74	−0.70	−0.89	−0.95	−1.10	−1.71	−1.35
b	0.99	1.03	1.07	1.03	1.05	0.97	1.03	1.02	1.14	1.12	0.13
s	−0.15	0.11	0.20	0.27	0.38	0.40	0.51	0.65	0.91	1.40	1.56
h	−0.22	−0.01	0.24	0.33	0.37	0.31	0.48	0.31	0.47	0.17	0.39
$t(a)$	−5.18	−4.60	−6.78	−7.76	−7.08	−7.03	−7.58	−6.57	−7.46	−8.14	−6.07
a	−0.46	−0.33	−0.50	−0.48	−0.42	−0.35	−0.34	−0.39	−0.22	−0.60	−0.14
b	1.00	1.03	1.04	0.99	1.00	0.93	0.94	0.98	1.06	1.16	0.15
i	−0.20	−0.14	−0.02	0.10	0.04	0.03	0.05	−0.05	−0.11	−0.07	0.13
p	0.05	−0.02	0.03	−0.04	−0.08	−0.17	−0.27	−0.34	−0.53	−1.04	−1.10
$t(a)$	−5.89	−3.48	−4.31	−4.26	−3.04	−2.62	−2.29	−2.28	−1.16	−2.28	−0.48
$t(b)$	50.81	31.62	30.65	34.99	25.94	26.29	23.87	21.33	19.47	14.74	1.86
$t(i)$	−4.12	−2.66	−0.40	1.65	0.47	0.50	0.61	−0.48	−1.04	−0.50	0.80
$t(p)$	2.60	−0.72	0.71	−1.02	−1.65	−3.53	−5.12	−6.23	−7.71	−9.53	−10.14

Table 6 : Summary Statistics and Factor Regressions for Monthly Percent Excess Returns on Deciles Formed on Earnings-to-Assets (ROA) and on Deciles Formed on Standardized Unexpected Earnings (SUE), 1/1972–12/2005, 408 Months

R_f is the one-month Treasury bill rate observed at the beginning of the month. The data on R_f, the Fama-French (1993) three factors are from Kenneth French's Web site. See the caption of Table 1 for the description of the investment factor INV and the productivity factor $PROD$. ROA is the quarterly earnings (COMPUSTAT quarterly item 8) divided by one-quarter-lagged assets (item 44, plus the difference between market equity and book equity multiplied by 0.10). This adjustment of quarterly assets, borrowed from Campbell, Hilscher, and Szilagyi (2007), is meant to mitigate the impact of assets close to zero when used to calculate ROA. At the beginning of every month from January 1972 to December 2005, we sort NYSE, Amex, and NASDAQ stocks into ten deciles based on the breakpoints of the ranked quarterly ROA from at least four months ago for stocks traded on all three exchanges. We use the four-month lag to be sure that the accounting information is known before the portfolio formation. Monthly value-weighted returns on the ten portfolios are calculated for the current month, and the portfolios are rebalanced monthly. For the SUE deciles, we rank all NYSE, Amex, and NASDAQ stocks into ten deciles at the beginning of every month by their most recent past SUE based on the breakpoints for stocks traded on all three exchanges. SUE is unexpected earnings (the change in quarterly earnings per share from its value four quarters ago) divided by the standard deviation of unexpected earnings over the last eight quarters. The portfolios are value-weighted.

	Low	2	3	4	5	6	7	8	9	High	H-L
	Panel A: ROA Deciles										
Mean	−0.74	−0.63	−0.40	−0.16	−0.13	−0.10	−0.03	0.00	0.11	0.26	0.99
Std	8.12	7.34	6.19	5.12	4.93	4.73	4.72	4.91	4.87	5.41	6.18
α	−1.40	−1.27	−0.96	−0.64	−0.62	−0.57	−0.51	−0.49	−0.38	−0.26	1.14
β	1.34	1.29	1.14	0.98	0.99	0.96	0.97	1.00	1.00	1.05	−0.29
$t(\alpha)$	−5.37	−5.75	−5.56	−5.30	−6.21	−6.56	−6.32	−5.35	−4.54	−2.07	3.77
a	−1.36	−1.15	−0.95	−0.78	−0.77	−0.69	−0.56	−0.42	−0.27	−0.07	1.30
b	1.11	1.10	1.05	1.03	1.05	1.02	1.00	0.98	0.96	0.97	−0.14
s	0.91	0.56	0.36	0.08	0.04	0.01	−0.03	−0.05	−0.06	−0.06	−0.97
h	−0.19	−0.27	−0.07	0.19	0.23	0.19	0.08	−0.10	−0.17	−0.30	−0.10
$t(a)$	−5.84	−5.70	−5.84	−6.06	−7.71	−7.71	−6.45	−4.29	−3.31	−0.55	4.79
a	−0.47	−0.36	−0.24	−0.41	−0.50	−0.57	−0.51	−0.52	−0.50	−0.35	0.12
b	1.15	1.11	0.99	0.95	0.97	0.96	0.97	1.00	1.02	1.05	−0.10
i	−0.27	−0.18	−0.19	0.09	0.02	0.01	0.03	−0.13	−0.07	−0.25	0.03
p	−0.97	−1.01	−0.77	−0.35	−0.16	−0.01	−0.02	0.12	0.19	0.27	1.25
$t(a)$	−2.06	−3.02	−2.40	−3.24	−4.38	−5.87	−6.06	−5.44	−5.93	−2.71	0.55
$t(b)$	19.68	34.06	37.27	27.60	34.41	34.87	33.07	35.06	58.22	36.87	−1.66
$t(i)$	−2.43	−2.60	−3.63	1.38	0.22	0.16	0.67	−2.29	−1.48	−4.17	0.24
$t(p)$	−8.19	−25.8	−20.83	−6.01	−3.01	−0.42	−0.62	3.51	6.96	5.40	12.16
	Panel B: SUE Deciles										
Mean	−0.59	−0.39	−0.21	−0.19	−0.15	0.07	0.21	0.41	0.41	0.47	1.06
Std	4.90	4.95	4.99	5.35	4.80	4.91	4.67	4.87	4.82	4.88	3.19
α	−1.08	−0.89	−0.70	−0.71	−0.64	−0.42	−0.26	−0.09	−0.07	−0.01	1.07
β	0.98	1.01	0.99	1.06	0.99	1.01	0.95	1.00	0.97	0.97	−0.01
$t(\alpha)$	−10.99	−10.01	−6.76	−6.43	−7.94	−4.95	−3.06	−1.03	−0.75	−0.06	6.61
a	−1.06	−0.85	−0.70	−0.65	−0.64	−0.46	−0.27	−0.08	−0.07	0.03	1.09
b	0.98	0.99	0.96	1.00	0.98	1.01	0.98	1.01	0.99	0.98	0.00
s	−0.03	−0.01	0.11	0.13	0.03	0.03	−0.11	−0.04	−0.05	−0.12	−0.09
h	−0.02	−0.07	−0.02	−0.12	0.00	0.04	0.03	−0.01	0.02	−0.04	−0.02
$t(a)$	−10.46	−8.87	−6.55	−5.51	−7.86	−4.77	−3.41	−0.91	−0.74	0.30	6.74
a	−0.87	−0.77	−0.49	−0.47	−0.62	−0.48	−0.39	−0.24	−0.1	−0.13	0.74
b	0.93	0.98	0.95	1.01	0.99	1.02	0.98	1.04	0.98	0.99	0.06
i	−0.23	−0.16	−0.13	−0.19	−0.02	0.08	−0.02	0.12	−0.06	0.01	0.24
p	−0.10	−0.05	−0.17	−0.18	−0.01	0.02	0.17	0.12	0.08	0.14	0.25
$t(a)$	−8.83	−8.12	−4.69	−3.72	−8.21	−5.28	−4.68	−2.85	−0.96	−1.30	4.86
$t(b)$	33.58	33.37	32.05	38.45	45.63	41.00	51.07	46.87	32.45	36.60	1.46
$t(i)$	−3.79	−2.97	−2.48	−2.79	−0.34	1.71	−0.33	2.42	−1.09	0.24	2.65
$t(p)$	−2.92	−1.32	−4.27	−2.92	−0.33	0.49	4.83	3.27	2.38	4.01	4.26

Table 7 : Summary Statistics and Factor Regressions for Monthly Percent Excess Returns on Deciles Formed on Earnings-to-Price (E/P), Cash Flow-to-Price (C/P), Dividend-to-Price (D/P), Prior 13–60 Month Returns (Reversal), and Past Five-Year Sales Growth (5-Yr SR), and Market Leverage (A/ME), 1/1972–12/2005, 408 Months

R_f is the one-month Treasury bill rate observed at the beginning of the month. The data on R_f, the Fama-French (1993) three factors, and portfolio returns on $E/P, C/P, D/P$, reversal deciles are from Kenneth French's Web site. See the caption of Table 1 for the description of the investment factor INV and the productivity factor $PROD$. Following Lakonishok, Shleifer, and Vishny (1994), we measure the five-year sales rank for June of year t, 5-Yr $SR(t)$, as the weighted average of the annual sales growth ranks for the prior five years, $\sum_{j=1}^{5}(6-j)\times \text{Rank}(t-j)$. The sales growth for year $t-j$ is the percentage change in sales (COMPUSTAT annual item 12) from year $t-j-1$ to $t-j$, $\log[\text{Sales}(t-j)/\text{Sales}(t-j-1)]$. Only firms with data for all five prior years are used to determine the annual sales growth ranks for years $t-5$ to $t-1$. To create the sales growth ranks, we sort firms into ten deciles in an ascending order on sales growth in each June, and then assign rank i, where $i=1,\ldots,10$, to a firm if its sales growth falls into the i^{th} decile. Following Fama and French (1992), we measure market leverage as the ratio of the book assets (item 6) to the market equity (price times number of shares). To form 5-Yr SR and A/ME deciles, we sort all NYSE, Amex, and NASDAQ stocks at the beginning of June of year t using the breakpoints of 5-Yr SR and A/ME measured at the fiscal yearend of $t-1$ for the stocks traded on all three exchanges. Monthly value-weighted returns on the portfolios are calculated from July of year t to June of year $t+1$.

	Low	2	3	4	5	6	7	8	9	High	H-L
	Panel A: E/P Deciles										
Mean	0.30	0.41	0.58	0.56	0.53	0.64	0.83	0.80	0.82	0.98	0.68
Std	6.07	4.92	4.75	4.49	4.60	4.46	4.38	4.47	4.74	5.38	4.88
α	−0.30	−0.09	0.11	0.11	0.07	0.22	0.41	0.38	0.39	0.50	0.81
β	1.23	1.02	0.95	0.91	0.92	0.86	0.84	0.85	0.87	0.97	−0.25
$t(\alpha)$	−2.59	−1.09	1.12	1.35	0.79	2.06	4.00	3.54	3.12	3.29	3.42
a	0.06	0.03	0.09	0.07	−0.08	−0.02	0.13	0.05	−0.03	−0.05	−0.11
b	1.05	1.00	0.99	0.96	1.02	0.99	1.00	1.00	1.06	1.19	0.13
s	−0.02	−0.15	−0.16	−0.13	−0.13	−0.04	−0.10	0.04	0.06	0.23	0.25
h	−0.57	−0.16	0.05	0.09	0.25	0.39	0.45	0.51	0.65	0.84	1.41
$t(a)$	0.71	0.35	0.93	0.91	−0.85	−0.27	1.59	0.59	−0.29	−0.48	−0.79
a	−0.06	−0.20	−0.08	−0.04	−0.07	0.00	0.11	0.18	0.25	0.32	0.38
b	1.16	1.03	0.98	0.94	0.94	0.91	0.91	0.90	0.91	1.02	−0.14
i	−0.37	−0.06	−0.03	0.01	0.01	0.15	0.23	0.19	0.17	0.19	0.56
p	−0.06	0.18	0.26	0.18	0.17	0.18	0.22	0.13	0.06	0.10	0.16
$t(a)$	−0.47	−2.48	−0.83	−0.51	−0.73	−0.03	1.12	1.62	1.88	2.08	1.57
$t(b)$	34.88	52.22	42.15	45.65	35.81	33.66	33.08	23.42	19.66	21.89	−1.96
$t(i)$	−5.84	−1.36	−0.60	0.32	0.19	2.26	4.40	3.37	2.10	2.01	4.06
$t(p)$	−1.48	7.01	6.10	6.11	3.79	3.53	4.63	2.80	0.94	1.21	1.44
	Panel B: C/P Deciles										
Mean	0.34	0.43	0.57	0.58	0.68	0.59	0.69	0.66	0.87	0.84	0.50
Std	5.87	4.90	4.70	4.77	4.56	4.49	4.44	4.50	4.39	5.05	4.48
α	−0.26	−0.06	0.09	0.11	0.23	0.16	0.27	0.26	0.47	0.38	0.64
β	1.20	1.01	0.96	0.97	0.91	0.87	0.85	0.83	0.80	0.92	−0.28
$t(\alpha)$	−2.48	−0.78	1.10	1.21	2.42	1.52	2.43	2.13	3.93	2.80	3.03
a	0.08	0.06	0.06	0.00	0.05	0.00	0.00	−0.09	0.05	−0.09	−0.17
b	1.06	0.98	1.00	1.04	1.01	0.99	0.97	1.01	0.99	1.10	0.04
s	−0.07	−0.16	−0.11	−0.09	−0.02	−0.15	0.03	−0.09	0.05	0.21	0.29
h	−0.52	−0.18	0.06	0.17	0.28	0.28	0.42	0.55	0.65	0.71	1.23
$t(a)$	1.04	0.81	0.75	0.06	0.57	0.00	0.02	−0.90	0.60	−0.80	−1.17
a	−0.11	−0.16	−0.07	−0.05	0.01	−0.15	0.06	0.00	0.32	0.36	0.48
b	1.16	1.02	0.99	1.00	0.97	0.94	0.90	0.89	0.84	0.93	−0.23
i	−0.29	−0.10	0.00	0.02	0.17	0.21	0.10	0.19	0.15	0.05	0.35
p	0.01	0.18	0.20	0.18	0.16	0.25	0.20	0.19	0.09	−0.01	−0.03
$t(a)$	−1.06	−1.90	−0.85	−0.57	0.07	−1.43	0.50	0.03	2.54	2.44	2.09
$t(b)$	39.96	45.26	49.76	43.51	38.90	37.31	30.48	23.38	20.09	19.10	−3.2
$t(i)$	−4.70	−2.54	−0.07	0.36	3.20	4.12	1.55	2.72	1.96	0.62	2.54
$t(p)$	0.42	6.41	6.70	4.00	3.91	5.58	3.91	3.31	1.55	−0.16	−0.26

	Low	2	3	4	5	6	7	8	9	High	H-L
	Panel C: D/P Deciles										
Mean	0.51	0.48	0.61	0.58	0.50	0.58	0.65	0.75	0.70	0.61	0.10
Std	5.85	5.19	5.12	4.86	4.72	4.61	4.41	4.34	4.04	4.00	5.53
α	−0.09	−0.04	0.11	0.11	0.06	0.15	0.24	0.36	0.36	0.36	0.45
β	1.20	1.06	1.02	0.96	0.90	0.88	0.84	0.80	0.69	0.50	−0.71
$t(\alpha)$	−0.86	−0.47	1.03	0.98	0.51	1.31	2.20	3.13	2.85	2.24	2.08
a	0.11	0.07	0.16	0.00	−0.09	−0.07	0.01	0.06	0.00	−0.13	−0.24
b	1.13	1.03	1.05	1.05	1.02	1.03	1.00	0.97	0.88	0.74	−0.39
s	−0.09	−0.11	−0.25	−0.14	−0.23	−0.20	−0.20	−0.13	−0.09	−0.04	0.05
h	−0.30	−0.16	−0.05	0.19	0.26	0.37	0.38	0.48	0.59	0.77	1.07
$t(a)$	1.14	0.80	1.56	−0.03	−0.80	−0.71	0.14	0.63	−0.03	−0.99	−1.37
a	−0.04	−0.09	−0.07	−0.22	−0.31	−0.2	−0.11	0.13	0.13	0.15	0.18
b	1.17	1.06	1.05	1.03	0.98	0.96	0.92	0.86	0.75	0.55	−0.62
i	−0.37	−0.19	−0.07	0.15	0.18	0.24	0.30	0.18	0.33	0.30	0.67
p	0.18	0.18	0.27	0.30	0.34	0.27	0.24	0.16	0.07	0.07	−0.11
$t(a)$	−0.36	−1.08	−0.67	−2.43	−2.75	−1.81	−1.00	1.05	1.01	0.81	0.76
$t(b)$	46.88	48.88	39.81	48.24	32.20	33.27	36.78	28.52	21.76	10.94	−9.37
$t(i)$	−7.23	−3.97	−1.09	3.22	3.11	4.13	5.12	2.76	4.52	3.28	5.71
$t(p)$	5.38	7.12	6.01	7.08	6.74	5.52	4.76	2.79	1.28	0.89	−1.13
	Panel D: Deciles Formed on Prior 13–60 Month Returns										
Mean	0.93	0.86	0.83	0.68	0.72	0.64	0.61	0.58	0.54	0.52	−0.41
Std	6.77	5.42	4.92	4.50	4.45	4.34	4.58	4.53	4.87	6.13	5.21
α	0.35	0.35	0.36	0.25	0.29	0.22	0.16	0.14	0.05	−0.10	−0.45
β	1.18	1.03	0.94	0.88	0.88	0.86	0.91	0.90	0.99	1.25	0.07
$t(\alpha)$	1.78	2.64	2.90	2.55	2.97	2.26	1.71	1.43	0.54	−0.92	−1.81
a	−0.06	0.04	0.10	0.00	0.07	0.03	0.03	0.07	0.06	0.18	0.24
b	1.18	1.09	1.01	0.98	0.99	0.97	1.01	0.98	1.03	1.13	−0.05
s	0.87	0.40	0.22	0.10	−0.05	−0.09	−0.15	−0.20	−0.20	−0.06	−0.93
h	0.51	0.43	0.38	0.38	0.35	0.32	0.23	0.14	0.01	−0.43	−0.94
$t(a)$	−0.40	0.33	0.92	−0.01	0.84	0.32	0.31	0.79	0.73	1.80	1.18
a	0.47	0.29	0.19	0.09	0.06	−0.01	−0.07	−0.09	−0.12	0.06	−0.41
b	1.18	1.06	0.99	0.93	0.93	0.91	0.96	0.95	1.02	1.20	0.02
i	0.33	0.24	0.26	0.21	0.21	0.18	0.12	0.09	−0.08	−0.41	−0.74
p	−0.37	−0.08	0.05	0.06	0.16	0.17	0.21	0.22	0.26	0.07	0.44
$t(a)$	2.30	1.99	1.40	0.86	0.56	−0.10	−0.74	−0.93	−1.38	0.53	−1.58
$t(b)$	21.31	24.79	25.49	31.54	35.41	32.25	42.56	36.69	47.75	37.39	0.24
$t(i)$	3.05	3.06	3.55	3.77	3.75	3.42	1.73	1.87	−1.89	−7.14	−5.60
$t(p)$	−4.52	−1.32	0.82	1.35	3.59	3.65	5.52	5.57	8.18	1.82	4.18

	Low	2	3	4	5	6	7	8	9	High	H-L
	Panel E: 5-Year SR										
Mean	0.35	0.22	0.15	0.10	0.01	0.07	0.00	0.19	−0.06	0.00	−0.35
Std	5.02	4.73	4.55	4.57	4.29	4.50	4.74	4.90	5.40	6.80	4.74
α	−0.11	−0.22	−0.28	−0.35	−0.41	−0.37	−0.48	−0.30	−0.60	−0.66	−0.55
β	0.93	0.90	0.87	0.91	0.85	0.90	0.98	1.00	1.11	1.35	0.42
$t(\alpha)$	−0.82	−1.90	−2.56	−3.66	−4.38	−4.13	−5.99	−3.36	−6.22	−4.60	−2.53
a	−0.42	−0.45	−0.51	−0.45	−0.48	−0.41	−0.44	−0.26	−0.45	−0.36	0.06
b	1.02	1.01	1.00	0.97	0.92	0.97	0.99	1.01	1.04	1.18	0.16
s	0.25	0.00	−0.07	−0.06	−0.18	−0.20	−0.12	−0.13	−0.04	0.08	−0.17
h	0.45	0.36	0.37	0.17	0.14	0.09	−0.04	−0.04	−0.24	−0.49	−0.94
$t(a)$	−3.30	−3.98	−5.25	−4.49	−5.61	−4.69	−5.71	−2.94	−4.78	−2.76	0.31
a	−0.38	−0.55	−0.53	−0.38	−0.58	−0.44	−0.45	−0.31	−0.38	−0.10	0.28
b	1.00	0.99	0.94	0.92	0.89	0.91	0.97	1.00	1.04	1.19	0.19
i	0.41	0.47	0.30	0.10	0.12	−0.06	−0.10	−0.15	−0.43	−0.76	−1.17
p	0.06	0.11	0.11	−0.02	0.13	0.12	0.02	0.11	0.01	−0.21	−0.27
$t(a)$	−2.64	−4.60	−4.54	−3.23	−5.85	−4.50	−5.58	−3.37	−4.18	−0.71	1.42
$t(b)$	23.62	34.90	34.38	39.73	35.85	38.29	51.96	48.71	43.67	37.50	3.51
$t(i)$	5.22	6.75	4.49	1.68	2.09	−1.22	−2.11	−3.20	−9.30	−10.6	−10.07
$t(p)$	1.30	2.22	2.08	−0.40	3.38	2.89	0.70	3.15	0.27	−3.81	−3.59
	Panel F: A/ME Deciles										
Mean	−0.20	−0.13	−0.01	0.12	0.21	0.16	0.26	0.23	0.35	0.37	0.57
Std	6.30	5.24	4.85	4.93	4.74	4.61	4.34	4.47	4.90	5.69	5.15
α	−0.79	−0.66	−0.50	−0.37	−0.25	−0.29	−0.15	−0.19	−0.09	−0.14	0.65
β	1.20	1.07	1.00	1.00	0.95	0.91	0.83	0.84	0.89	1.03	−0.17
$t(\alpha)$	−4.98	−7.14	−5.90	−4.10	−2.57	−2.92	−1.42	−1.67	−0.70	−0.90	2.62
a	−0.32	−0.50	−0.50	−0.42	−0.38	−0.53	−0.46	−0.59	−0.60	−0.63	−0.32
b	1.00	1.02	0.99	1.04	1.02	1.02	0.97	1.02	1.08	1.18	0.18
s	−0.13	−0.10	0.03	−0.04	−0.04	0.04	0.04	0.06	0.25	0.38	0.50
h	−0.73	−0.23	0.00	0.09	0.20	0.37	0.48	0.63	0.75	0.73	1.45
$t(a)$	−2.56	−5.50	−5.59	−4.60	−3.91	−5.82	−5.37	−7.56	−6.35	−5.02	−1.95
a	−0.50	−0.52	−0.51	−0.43	−0.37	−0.33	−0.28	−0.32	−0.15	−0.15	0.35
b	1.12	1.03	0.99	1.01	0.97	0.92	0.87	0.87	0.91	1.05	−0.07
i	−0.44	−0.31	−0.11	0.04	0.09	0.07	0.21	0.17	0.19	0.32	0.76
p	−0.07	0.03	0.09	0.05	0.08	0.00	0.03	0.05	−0.06	−0.19	−0.12
$t(a)$	−2.97	−5.29	−5.65	−4.15	−3.59	−3.10	−2.53	−2.45	−0.99	−0.80	1.28
$t(b)$	26.64	47.90	46.69	41.13	34.66	32.85	28.31	25.15	21.69	19.63	−0.89
$t(i)$	−4.67	−5.43	−2.31	0.67	1.48	1.28	3.30	2.38	2.23	3.50	5.06
$t(p)$	−1.24	0.92	2.65	1.14	1.79	−0.04	0.55	0.81	−0.80	−2.35	−1.10

Table 8 : Economic Fundamentals for Deciles Formed on Campbell-Hilscher-Szilagyi's (2007) Failure Probability Measure (F-Prob), Ohlson's (1980) O-Score, Earnings-to-Assets (ROA), Standardized Unexpected Earnings (SUE), Earnings-to-Price (E/P), Cash Flow-to-Price (C/P), Dividend-to-Price (D/P), Prior 13–60 Month Returns (Reversal), and Past Five-Year Sales Growth (5-Yr SR), and Market Leverage (A/ME), 1/1972–12/2005, 408 Months

ROA is quarterly percent earnings (COMPUSTAT quarterly item 8) divided by one-quarter-lagged assets (item 44, plus the difference between market equity and book equity multiplied by 0.10). The adjustment of quarterly assets, borrowed from Campbell, Hilscher, and Szilagyi (2007), is meant to mitigate the impact of assets close to zero when used to calculate ROA. I/A (in annual percent) is the annual change in gross property, plant, and equipment (COMPUSTAT annual item 7) plus the annual change in inventories (item 3) divided by the lagged book value of assets (item 6). Portfolio ROA and I/A are value-weighted ROAs and I/As of all the stocks in the portfolio, respectively, where the weights are provided by their market equity. The breakpoints for the $E/P, C/P, D/P$, and reversal portfolio deciles are from Kenneth French's Web site. The caption of Table 5 describes the formation of the F-Prob and O-score portfolios, the caption of Table 6 describes the formation of the ROA and SUE portfolios, and the caption of Table 7 describes the formation of the 5-Yr SR and A/ME portfolios.

	Low	2	3	4	5	6	7	8	9	High	H-L
Panel A: Means and Standard Deviations of Quarterly Percent ROA for the Distress and Earnings Deciles											
	F-Prob Deciles										
Mean(ROA)	2.80	2.37	2.01	1.58	1.30	0.88	0.58	0.01	−1.10	−3.08	−5.88
Std(ROA)	0.52	0.37	0.37	0.40	0.56	0.56	0.71	1.29	1.85	4.77	4.66
	O-Score Deciles										
Mean(ROA)	2.42	1.49	1.23	0.94	0.73	0.41	−0.08	−0.71	−1.49	−5.15	−7.54
Std(ROA)	0.41	0.56	0.51	0.62	0.68	0.82	1.09	1.75	1.86	6.44	6.33
	ROA Deciles										
Mean(ROA)	−7.51	−1.54	−0.10	0.52	0.89	1.25	1.62	2.08	2.74	4.15	11.67
Std(ROA)	6.45	1.62	0.77	0.45	0.34	0.30	0.28	0.28	0.29	0.45	6.53
	SUE Deciles										
Mean(ROA)	1.00	1.41	1.44	1.58	1.64	1.72	1.88	1.92	1.92	2.22	1.22
Std(ROA)	1.03	0.61	0.59	0.49	0.43	0.43	0.41	0.42	0.41	0.55	1.20
Panel B: Means and Standard Deviations of Annual Percent I/A for the Additional Value Deciles											
	E/P Deciles										
Mean(I/A)	11.58	10.65	9.81	9.05	8.03	8.24	8.33	8.83	8.23	8.59	−2.99
Std(I/A)	4.66	4.03	3.58	4.46	6.32	4.34	3.59	5.23	3.42	4.31	6.24
	C/P Deciles										
Mean(I/A)	13.54	10.25	9.95	9.05	8.95	9.26	8.55	9.56	8.88	7.70	−5.84
Std(I/A)	4.91	3.86	4.50	3.94	4.84	5.08	4.76	6.35	4.48	3.89	6.50
	D/P Deciles										
Mean(I/A)	15.11	11.02	8.85	8.24	7.98	6.76	7.70	6.66	6.93	5.80	−9.3
Std(I/A)	4.57	3.58	3.52	4.16	4.10	3.82	4.34	4.92	3.18	4.29	5.66
	Deciles Formed on Prior 13–60 Month Returns										
Mean(I/A)	3.93	4.09	5.86	6.46	7.38	8.00	8.93	9.23	11.36	16.34	12.41
Std(I/A)	5.49	5.85	4.48	4.02	3.60	3.50	3.53	3.70	4.09	5.43	7.01
	5-Yr SR Deciles										
Mean(I/A)	4.86	5.87	5.40	6.87	7.45	8.34	8.87	10.07	11.53	17.32	12.46
Std(I/A)	5.60	3.95	3.18	3.29	3.27	5.19	3.42	3.42	4.13	6.37	8.01
	A/ME Deciles										
Mean(I/A)	15.70	11.79	10.17	9.48	8.76	7.85	7.40	5.95	5.07	5.30	−10.4
Std(I/A)	6.78	4.23	3.36	4.38	3.76	2.81	2.70	4.09	2.83	4.67	8.74

Figure 2 : Event-Time and Calendar-Time Evolution of Earnings-to-Assets (ROA) and Investment-to-Assets (I/A) for the 25 Size and Book-to-Market Portfolios, 1972:Q1 to 2005:Q4, 136 Quarters

In Panels A and D, for each portfolio formation year $t = 1972$ to 2005, we calculate the quarterly ROAs for $t+q, q = -20, \ldots, 20$ and the annual I/As for $t+y, y = -5, \ldots, 5$. The ROA for $t+q$ and the I/A for $t+y$ are then averaged across portfolio formation years t. ROA is quarterly earnings (COMPUSTAT quarterly item 8) divided by one-quarter-lagged assets (item 44, plus the difference between market equity and book equity multiplied by 0.10). The adjustment of quarterly assets, borrowed from Campbell, Hilscher, and Szilagyi (2007), is meant to mitigate the impact of assets close to zero in calculating ROA. I/A is the annual change in gross property, plant, and equipment (COMPUSTAT annual item 7) plus the annual change in inventories (item 3) divided by the lagged book value of assets (item 6). We follow Fama and French (1996) in constructing the 25 size-BE/ME portfolios. Small-Growth is the portfolio of stocks in the smallest size and lowest BE/ME quintiles; Small-Value is the portfolio of stocks in the smallest size and highest BE/ME quintiles; Big-Growth is the portfolio of stocks in the biggest size and lowest BE/ME quintiles; and Big-Value is the portfolio of stocks in the biggest size and highest BE/ME quintiles. We plot the median ROAs and I/As for the four extreme portfolios.

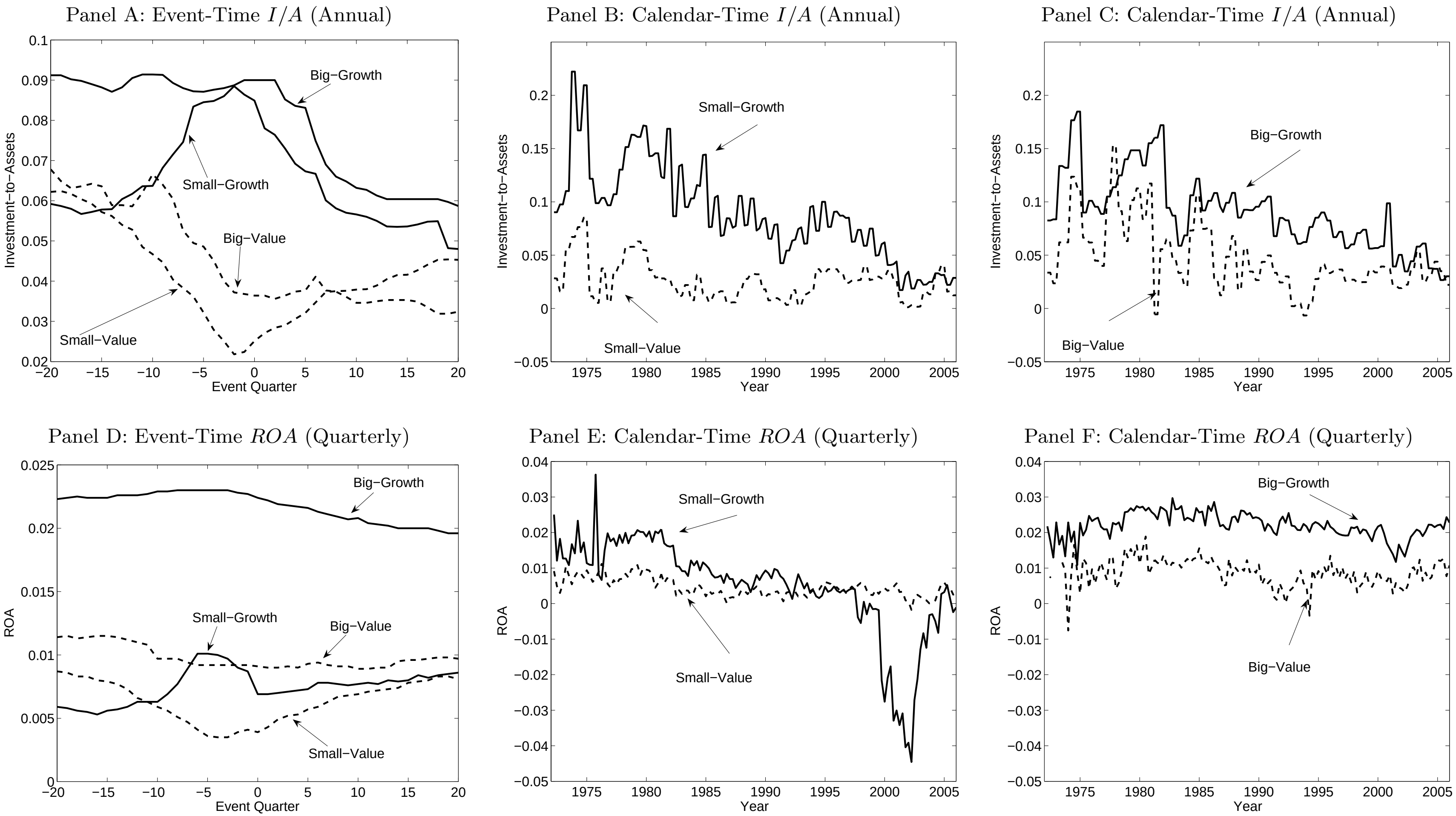

Figure 3 : Event-Time and Calendar-Time Evolution of Earnings-to-Assets (ROA) and Investment-to-Assets (I/A, Contemporaneous and Lagged) for the 25 Size and Momentum Portfolios, 1972:Q1 to 2005:Q4, 136 Quarters

The 25 size-momentum portfolios are constructed as described on Kenneth French's Web site. The portfolios are constructed monthly as the intersections of five quintiles formed on market equity and five quintiles formed on prior 2–12 month returns. The monthly size breakpoints are the NYSE size quintiles, and the monthly momentum breakpoints are NYSE quintiles. In Panels A and D, for each portfolio formation month t = January 1972 to December 2005, we calculate quarterly ROAs and annual I/As for $t+m, m = -60, \ldots, 60$. The ROA and I/A for $t+m$ are then averaged across portfolio formation months t. ROA and I/A are defined in the caption of Figure 2. ROA is the most recent ROA relative to portfolio formation month t. In Panels D and E, I/A is the current yearend I/A relative to month t. For example, if the current month is March 2003, then I/A is measured at the end of year 2003. In Panel F, I/A (lagged) is the I/A value on which an annual sorting on I/A in each June is based. For example, if the current month is March 2003, then I/A (lagged) is the I/A at the yearend of 2001; if the current month is September 2003, then I/A (lagged) is the I/A at the yearend of 2002. Small-Loser is the portfolio of stocks in the smallest size and lowest momentum quintiles; Small-Winner is the portfolio of stocks in the smallest size and highest momentum quintiles; Big-Loser is the portfolio of stocks in the biggest size and lowest momentum quintiles; and Big-Winner is the portfolio of stocks in the biggest size and highest momentum quintiles.